Three Essays on the Syndicated Loan Market

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Introduction

An introductory summary

Syndicated loans are an important source of external financing for large corporations. This thesis studies three important aspects of the syndicated loan market: (i) the impact of the ability to unload loan risk via traded credit default swap (CDS) contracts on the fraction of loans retained by lead banks, (ii) the impact of managerial traits on the design of syndicated loan contracts, and (iii) the impact of long-term lending relationships on the decision to include contract provisions in loan contracts that stipulate that the coupon paid rises if the firm's financial performance deteriorates and/or vice versa.

The first paper, "Loan Sales versus Credit Default Swaps — The Promise and Perils of Financial Innovation", analyzes the impact of the ability to unload loan risk via traded CDS contracts on primary loan market allocation. Theoretically, there is a clear prediction on how CDS trading will affect loan sales: Banks are less likely to sell loans once credit protection via CDS is available. However, there are different economic mechanisms that can lead to this conjecture. Duffee and Zhou (2001) argue that tailor-made CDS are a flexible tool to temporarily lay off credit risk and hence (partially) replace loan sales. Parlour and Winton (2013) argue that CDS trading has a detrimental effect on loans sales as banks can no longer commit to monitor borrowers if credit risk can be laid off via CDS. Hence, loan sales become more difficult/costly and originating banks are forced to retain larger shares in their loans.

I compare loans to firms before and after CDS are actively traded on a borrower's debt with loans to firms that never have actively traded CDS on their debt. The results indicate that banks retain significantly larger shares of loans after CDS trading becomes available. The effects is also meaningful economically, that is, banks retain on average 7% more of a loan if hedging via CDS is possible. In the next step, I explicitly disentangle the risk management from the moral hazard effect by analyzing the effect of CDS trading on syndicate structure for different types of firms and lenders. Overall, the findings do not support the claim that the moral hazard effect is a significant concern in the syndicated loan market. The results suggest that banks actively use CDS as a risk management tool and therefore rely less on other risk sharing mechanisms.

The second paper, "Managerial Optimism and Debt Contract Design" (co-authored with Tim R. Adam, Valentin Burg, and Tobias Scheinert), analyzes how managerial traits impact debt contract design. In particular, we analyze performance-sensitive debt contracts (PSD), that is, debt contracts with coupon payments that deterministically follow an underlying measure of borrower quality. If borrower quality decreases, coupon rates are increased to pre-agreed levels. This option, which is valuable for the lender, is reflected in a lower initial spread paid by the borrower on performance-sensitive loans when compared to straight debt. Manso, Strulovici, and Tchistyi (2010) predict that PSD serves as a screening device for lenders: high quality borrowers select PSD contracts as they perceive the risk of having to pay a higher spread in the future as low, and low quality borrowers select straight debt contracts. In their model, Manso et al. (2010) assume that the manager of a firm correctly assesses the quality of his/her firm and chooses the optimal debt contract given his/her expectations. However, the recent literature questions this assumption (e.g., Malmendier and Tate (2005)). In particular, overly optimistic managers could persistently overestimate the firms' quality, while rational managers correctly assess the firms' quality on average. We argue that firms with overly optimistic managers are more likely to issue PSD contracts than their rational counterparts.

Our empirical evidence confirm this prediction. Firms with optimistic managers are more likely to choose debt contracts with performance-pricing features than rational managers. Further, within the set of PSD contracts, optimistic managers choose PSD contracts that contain more risk-compensation than rational managers. Consistent with an overestimation of firm quality, we find that firms with optimistic managers are significantly more likely to experience a performance deterioration after a PSD issue than firms with rational managers. Overall, our findings indicate that managerial optimism is an important determinant of debt contract design.

The third paper, "Hold-Up and the Use of Performance-Sensitive Debt" (co-authored with Tim R. Adam), examines whether PSD is used to reduce hold-up problems in long-term lending relationships. A lender acquires reusable, proprietary information on the borrower over the course of a lending relationship and hereby gains an informational advantage vis-à-vis other potential lenders. Sharpe (1990) and Rajan (1992) argue that the non-verifiable inside information that the lender acquires can generate hold-up problems. The information advantage by the relationship lender makes it difficult for the borrower to switch to another, less well informed, lender due to adverse selection. This can be strategically exploited by the relationship lender, for example, by raising the interest rate. Von Thadden (1995) shows that a solution to this problem is to specify contract terms ex ante, thereby limiting the discretion of the lender. One can view PSD contracts as limiting the discretion of lenders because by pre-specifying the loan contract terms if a borrower's performance deteriorates or improves PSD avoids debt renegotiation in these states. For example, rather than renegotiate a loan after a covenant violation, the performance-pricing provision specifies the outcome of such renegotiation ex ante and thus avoids the situation of a technical default.

Our results indicate that PSD contracts are more likely to be used in repeated lending relationships. We further document that the use of PSD varies systematically across different types of borrowers. Santos and Winton (2008) argue that the costs of relationship lending are higher for companies, which do not have access to other financing sources (e.g., bond market access). In line with this argument, we find that PSD contracts are more common in relationship lending arrangements with smaller firms, firms that do not have a long-term issuer credit rating at the time of the loan origination, and firms with lower analyst coverage. Overall, our results are indicative of PSD being used to mitigate hold-up concerns in long-term lending relationships.

The three thesis chapters contribute to the literature on bank and firm behavior in the syndicated loan market.

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Loan Sales versus Credit Default Swaps — The Promise and Perils of Financial Innovation

Daniel Streitz

Abstract:

This study analyzes the impact of credit default swap (CDS) trading on loan sales and the structure of loan syndicates. Theoretically, CDS can have both positive and negative effects on the loan market. One the one hand, CDS are a flexible risk management tool and can therefore (partially) replace loan sales (*risk management effect*). On the other hand, lenders can no longer credibly commit to monitor a borrower if laying off credit risk anonymously via CDS is possible making loan sales costly (*moral hazard effect*). We find that lenders retain significantly higher shares of loans once CDS are actively traded on a borrower's debt and the overall syndicate becomes more concentrated. These effects are stronger if CDS liquidity is higher. Disentangling the risk management from the moral hazard effect, we find that potentially negative effects of CDS trading are of minor importance in the syndicated loan market. The results are robust to controlling for the potential endogeneity of CDS introduction.

Keywords: Loan Sales, Credit Default Swaps, Syndicate Structure, Syndicated Loans

JEL-Classification: G21, G32

1 Introduction

Despite the growing importance of credit derivatives in recent years, the impacts of this financial innovation on the nature and operation of credit markets are not yet fully understood. While the majority of CDS have corporate bonds as underlying instruments, credit derivatives can also be used to trade otherwise non-marketable credit risks such as bank loans (Duffee and Zhou (2001), Instefjord (2005)). Theoretically, the enhanced risk sharing via CDS can alleviate credit supply frictions with potentially positive effects on firm's credit terms and overall credit supply. However, empirical evidence so far does not confirm this prediction.[1] Also empirical research on how and to what extent banks use CDS to manage credit risk is scarce.

One important determinant of the effects of CDS on credit markets is the interplay with bank's existing risk management tools such as loan sales. A bank can limit the exposure to a borrower to comply with regulatory capital requirements and diversify the loan portfolio by (partially) selling loans (Dennis and Mullineaux (2000)) — e.g. via syndication. Theoretically the effect of CDS trading on loan sales is unambiguous: Banks are less likely to sell loans once credit protection via CDS is available. However, there are different economic mechanisms that can lead to this conjecture. Duffee and Zhou (2001) argue that tailor-made CDS are a flexible tool to temporarily lay off credit risk and hence (partially) replace loan sales. Parlour and Winton (2013) argue that CDS trading has a detrimental effect on loans sales as banks can no longer commit to monitor borrowers if credit risk can be laid off via CDS. Hence, loan sales become more difficult/costly and originating banks are forced to retain larger shares in their loans.

[1] For example, Hirtle (2009) shows that CDS trading has only limited effects on bank loan supply. Ashcraft and Santos (2009) show that CDS trading does not affect the spreads that firms pay to raise funding via loans or bonds.

We empirically analyze the impacts of CDS trading on *primary*[2] loan sales using a large sample of syndicated loans[3] and explicitly disentangle risk management from moral hazard effects. In particular, we compare the syndicate structure of loans to borrowers before and after CDS are actively traded on the borrower's debt with the syndicate structure of loans to borrowers that never have actively traded CDS on their debt during the sample period.

We start by establishing a general link between CDS trading, loan sales and syndicate structure. Consistent with existing theories, lead banks sell seven percentage points less of a loan once credit protection via CDS is available, which is economically important given an average lead share of 38%. However, consistent with the argument that the flexibility of the underlying CDS contract matters, lead arrangers only sell a lower fraction of the loan if CDS liquidity is sufficiently high, i.e. the bid-ask spread is low.

This evidence is both consistent with the idea that CDS are a substitute for loan sales and the idea that CDS increase moral hazard problems in loan syndicates. We disentangle both effects empirically by analyzing the effect of CDS trading on syndicate structure for different types of firms and lenders. If the moral hazard effect is the dominant effect, then this problem should be especially severe for borrowers that require intensive monitoring, e.g. riskier, more opaque firms. However, we do not find any empirical support for this conjecture. The effect of CDS trading on syndicate structure does not differ for low or high risk borrowers and for more or less opaque borrowers. We further test, if the effect of CDS trading is different for relationship loans. Sufi (2007) argues that previous lending relationships between the borrower and the lead arranger can serve as a measure of the information advantage of the

[2] We control for a possible effect of secondary market trading in the robustness section.

[3] In a syndicated loan, the originating bank (lead bank) negotiates the deal with the borrower and then decides upon which fraction of the loan to sell to other participating lenders. Primary loan sales are mainly done via syndication. We therefore use the terms syndication and loan sales synonymously in this study when we analyze the share retained by the lead arranger.

lead arranger with respect to participant lenders. Moral hazard should be less severe if a lending relationship exists because the lead arranger has already put in the effort required to learn about the firm. Again, we do not find different effects for relationship vs. non relationship loans. Finally, we test the effect of lender reputation. As shown theoretically by Parlour and Winton (2013), moral hazard problems arising from CDS trading are less severe if the lender's reputation is high. Our results show that effect of CDS trading on syndicate structure is not significantly different for lenders with different levels of reputation.

We further analyze which banks end up as syndicate members and whether the syndicate participant selection process is different after CDS are actively traded on the borrowers debt. The main argument is that the degree of information asymmetry between a potential participant and the lead bank is not the same for all potential participants. Hence, moral hazard concerns are more severe for some banks compared to others. For example, a bank that already knows the borrower from previous deals is less dependent on the information generation and monitoring by the lead bank. Therefore, this bank may decide to participate in a syndicate even if CDS availability prevents the lead bank from credibly committing to monitor the borrower. On the contrary, banks that do not know the borrower and the lead arranger should be especially reluctant to invest in a syndicated loan if the lead bank cannot credibly commit to monitor the borrower. We find — consistent with Sufi (2007) — that in general banks that already know the borrower from prior deals and banks that are located in the same region as the borrower are significantly more likely to end up as syndicate members compared to other banks. Further, also banks that already know the lead arranger from prior deals are more likely to participate in a syndicate compared to other banks. However, the syndicate participant selection process is not significantly different for loans in which CDS are actively traded on the borrowers debt which is unsupportive of the conjecture that CDS trading amplifies moral hazard problems. Overall, the results show that an increase in moral hazard caused by CDS introduction is not a major concern in the syndicated loan market.

CDS trading and the timing of CDS inception is clearly endogenous, hence this problem needs to be addressed in order to make causal inferences about the effect of CDS trading on the structure of loan syndicates and loan sales. Firms that have actively traded CDS on their debt are different from firms that do not have actively traded CDS on their debt, therefore, unobservable differences could drive both CDS introduction, as well as changes in the loan syndicate structure. Further, as noted by Subrahmanyam, Tang, and Wang (2014), the timing of CDS inception may be endogenous. We address these concerns by constructing a model to predict CDS trading and use this model to run an instrumental variable estimation. Minton, Stulz, and Williamson (2008) show that banks that use foreign exchange derivatives are more likely to be net buyers of CDS, i.e. are more prone to use derivatives in general. Therefore, foreign exchange derivatives holdings are likely to be correlated with investor demand for credit protection via CDS. We follow Saretto and Tookes (2013) and Subrahmanyam et al. (2014) and use the average amount of foreign exchange derivatives held by all the lead arrangers that lend money to a company in the previous five years as a fraction of the total loans of the lead arrangers as an instrument for CDS trading. This variable is constructed at the firm level for each year. As foreign exchange hedges are macro hedges, it is unlikely that this variable is directly related to the loan (and borrower) specific syndicate structure. Overall, our results are robust to potential endogeneity concerns.

We contribute to the literature by providing novel evidence that banks actively use CDS as a risk management tool and therefore rely less on other risk sharing mechanisms. Understanding the trade-off between different risk management tools is important to better understand under which conditions CDS trading reduces credit supply frictions. If CDS trading replaces existing risk management tools it is unlikely to have a strong impact on credit supply by banks and loan contract terms. This is consistent with existing studies, which find limited effects of CDS trading on credit markets (Hirtle (2009), Ashcraft and Santos (2009)).[4] We further show that potentially negative effects of CDS trading — increased moral hazard problems — are of minor importance.[5]

We also add to the literature on loan syndicate structure by showing that the availability of other risk management tools significantly affects syndicate composition. Sufi (2007) and Dennis and Mullineaux (2000) show that lenders form more concentrated syndicates when borrowers are more opaque. Bharath, Dahiya, and Hallak (2012) show that an increase in shareholder rights makes loan syndicates more concentrated as firm's risk shifting incentives increase. Gatev and Strahan (2009) show that commercial banks dominate the market for lines of credit as they have an advantage over other investors in managing liquidity risk. Gopalan, Nanda, and Yerramilli (2011) show that banks ability to syndicate loans decreases after a negative shock to their reputation.

The rest of the paper is organized as follows. In Section 2, we discuss the theoretical background and derive empirical hypothesis. Section 3 describes our sample selection process. The main empirical analysis, demonstrating a link between CDS trading, loan sales and the structure on loan syndicates,

[4] Several studies analyze the effect of CDS trading on the bond market. E.g., Das, Kalimipalli, and Nayak (2014) find no evidence for an increase in bond market liquidity or a reduction in pricing errors. Chava, Ganduri, and Ornthanalai (2012) show that credit ratings become less important when a market price for the risk of a company can be observed. Saretto and Tookes (2013) analyze how the capital structure of companies is affected by CDS trading and find that firms maintain higher leverage ratios and longer debt maturities once CDS are available.

[5] Ashcraft and Santos (2009) also analyze the effect of CDS trading on the share retained by the lead arranger in an earlier version of the paper (Ashcraft and Santos (2007)). We differ from this analysis in several fundamental ways. First, and most importantly, we explicitly distinguish between moral hazard and risk management effects. Second, we address the endogeneity of CDS introduction. Third, we analyze a much larger sample — the analysis by Ashcraft and Santos (2007) is based on a sample of 291 loan contracts.

is presented in Section 4. We disentangle the moral hazard from the risk management effect in Section 5. Section 6 presents robustness tests and Section 7 concludes.

2 Theoretical Framework

In a Modigliani-Miller world, bank risk management does not increase firm value as shareholders can manage risks more efficiently by holding a well-diversified portfolio. However, market frictions such as moral hazard and adverse selection problems lead banks to acquire borrower specific private information that can make bank loans illiquid and loan sales difficult. The existence of private information makes bank failures costly (see e.g. Goderis, Marsh, Castello, and Wagner (2007), Cebenoyan and Strahan (2004)). Further, banks are required by regulation (e.g. the Basel Accords) to implement risk management tools and hold equity capital to back-up risky assets. Overall, banks have strong incentives to actively manage the risk of their loan portfolio.[6]

One way how banks can manage credit risk is syndication. In a syndicated loan, the lead bank negotiates the deal with the borrower and then decides upon which fraction of the loan to sell to other participating lenders. Thereby, the bank can limit the size of any single loan to comply with regulatory capital requirements and diversify the loan portfolio by taking smaller shares in multiple syndicated loans (Dennis and Mullineaux (2000)).[7]

Recently more and more firms that borrow from banks have actively traded CDS on their debt. The CDS market is an over-the-counter derivative market where default protection for corporate bonds and loans can be bought. Banks that have access to credit derivatives therefore have an alternative tool

[6] See also Froot and Stein (1998) and Froot, Scharfstein, and Stein (1993).

[7] Consistent with the risk sharing motive for loan syndication, Dennis and Mullineaux (2000) find that banks are more likely to syndicate larger loans and loans with longer maturities.

to manage the risk associated with a loan. The question that arises is whether and how a market in which loan sales/syndication exist is affected by the availability of CDS?

Duffee and Zhou (2001) show theoretically that CDS can be a more flexible tool to manage credit risk compared to loan sales if the banks informational advantage is non constant over the life of the loan. The lead bank is considered an "informed lender" that knows more about the true credit quality of the borrower than the potential participants (Diamond (1984)). The arising adverse selection problems make loan sales costly. Gorton and Pennachi (1995) show that banks will only sell loans if the banks' internal funding cost are sufficiently high and/or the cost of funding loans via loan sales is sufficiently small (e.g. high quality borrowers). If the banks informational advantage varies over the life of a loan as in Duffee and Zhou (2001), it is therefore optimal for the bank to lay off a larger (smaller) part of the credit risk when information asymmetry is low (high). Thereby, the bank can minimize the costs of adverse selection. Duffee and Zhou (2001) show that tailor-made CDS are a flexible tool to temporarily lay off credit risk. Loan sales on the other hand are less flexible as the loan is no longer on the bank's balance sheet. CDS can therefore be value creating and (partially) replace loan sales.

Hypothesis 1: Risk management via CDS is more flexible than risk management via loans sales. Therefore, banks retain larger shares of a loan once credit derivatives are actively traded on a borrower's debt.

Sufi (2007) argues (building on the models of Holmstrom (1979), Holmstrom and Tirole (1997), and Gorton and Pennachi (1995)) that moral hazard problems exist in syndicated loans. The "informed" lead arranger is able to monitor and learn about the borrower through unobservable and costly effort. Participants, on the other hand, are "uninformed lenders" who rely on the monitoring effort by the lead arranger. The lower the share of a loan that is retained by the lead arranger, the lower are the incentives to actively monitor the borrower. As potential participants are aware of this problem, they are only willing to invest if the lead arranger retains a large enough fraction of the loan to credibly commit to monitor the borrower. As shown by Parlour and Winton (2013), retaining a larger share of the loan is no longer a credible signal by the bank if CDS are available. The lead arranger can lay off credit risk anonymously via CDS which effectively reduces the incentive to monitor. Without a credible signal by the lead arranger, potential investors are less willing to participate in a syndicated loan. Hence, syndication becomes less likely and the lead arranger has to retain a larger share of the loan.

Hypothesis 2: A commitment to monitor the borrower is less credible if laying off credit risk via CDS is possible, hence investors are less willing to participate in a syndicated loan. Therefore, banks retain larger shares of a loan once credit derivatives are actively traded on a borrower's debt.

Note that both *Hypothesis 1* and *Hypothesis 2* predict that the lead lender will sell a smaller fraction of the loan. However, the reasons differ: *Hypothesis 1* predicts that the lender will (partially) substitute loan sales via the purchase of CDS. *Hypothesis 2* predicts that loan sales become more difficult because the lender can no longer credibly commit to monitor the borrower if CDS are available. Which effect prevails is an empirical question that will be addressed in the following analysis.

3 Data

We follow Saretto and Tookes (2013) and use all USD denominated CDS spreads for all maturities obtained from Bloomberg to identify firms that have actively traded CDS on their debt. For robustness checks, we additionally use USD denominated CDS spreads from the CMA database. We manually match all reference entity names to the borrower names in the Thomson Reuters Loan

Pricing Corporation Dealscan database (LPC Dealscan), that contains detailed information on corporate loan contracts. We restrict the sample to loans to (non financial) US borrowers originated between 2000 and 2010.[8] We further exclude loans with missing information on the maturity, the all-in-drawn spread, or the deal amount. We also exclude all loans by firms that have actively traded CDS on its debt at any time during the sample period but only issue loans before or after the CDS introduction. Note that, as common in the literature (e.g. Berg, Saunders, and Steffen (2013), Bharath, Dahiyab, Saunders, and Srinivasan (2007)), the loan panel is created on the facility (tranche) level. Following Sufi (2007), we classify a lender as a lead-lender if the variable called "Lead Arranger Credit" (provided by LPC's Dealscan) takes on the value "Yes" or if the lender is the only lender specified in the loan contract. Finally, we merge the loan data to Standard and Poor's Compustat North America database to obtain financial information on the borrowers.[9]

Dedependent Variables: Syndicate Structure Indicators

Following Sufi (2007), we use the percent of the total loan held by the lead bank (*% Held By Lead*) as the main characteristic of the syndicate. *% Held By Lead* is larger (lower) if the lead arranger sells a lower (larger) fraction of the loan. We use two additional variables to also capture any effects on the overall syndicate structure, i.e. including particiapting banks. *Herfindahl*, a measure for the syndicate concentration, is calculated by squaring the shares of the loan for each syndicate member and summing up the squared shares for all the lenders in each particular facility. The Herfindahl index can take on values between (nearly) 0 (a large number of banks holding small shares of the loan) to 10,000 (one bank holds the entire loan amount). Additionally,

[8] Loans issued prior to 2000 are excluded as the vast majority of CDS introduction dates are after 2000. However, not imposing this restriction and using all loans originated between 1990 and 2010 yields qualitatively similar results.

[9] We use Michael Robert's Dealscan-Compustat Linking Database to merge Dealscan with Compustat (see Chava and Roberts (2008) for details).

as in Bharath et al. (2012), we also use the number of members in the loan syndicate.

Main Independent Variables: CDS Trading Indicators

We follow Ashcraft and Santos (2009) and Subrahmanyam et al. (2014) and construct two CDS trading variables. One is *CDS Traded*, a dummy that equals one if a firm has actively traded CDS on its debt at any point in time during the sample period and zero otherwise. This dummy is a firm fixed effect that is used to control for unobservable differences between firms with and without CDS. The other variable is *CDS Trading*, a dummy that equals one if a firm has active CDS trading at the time of the loan origination date and zero otherwise. *CDS Trading* is the primary variable of interest as it captures the marginal impact of CDS introduction on the syndicate structure.

Control Variables

Throughout the analysis we control for various firm characteristics and loan characteristics. Included are the firm size, specified as *ln(Total Assets)*, the market-to-book asset ratio (*Market-To-Book*), and proxies for firm risk and profitability. We further control for the maturity of the loan (*ln(Maturity)*), the loan amount (*ln(Facility Amount)*), and other loan characteristics. All control variables are defined in more detail in the Appendix Table A.I.

Table 1 presents descriptive statistics for the final panel. The sample comprises 14,190 facilities to 3,265 distinct borrowers. Thereof 288 companies have actively traded CDS at some point in time during the sample period. Panel A reports descriptives for two CDS trading indicators. 19% of loans are issued by borrowers that have CDS trading at some point in time during the sample period. For 9% of the loans the borrower has actively traded CDS at the time of the loan issue. Panel B reports descriptives for the syndicate structure indicators. The median share of the loan retained by the lead arranger is 28%

which consistent with prior studies (e.g. Bharath et al. (2012)). The median syndicate Herfindahl index is 1,547 and the median number of lenders is 5. The number of observations is reduced for the variables *% Held By Lead* and *Herfindahl*, as the individual shares retained by the lenders are not reported for all loans that are included in the Dealscan database.[10] Panel C reports loan characteristics, which are consistent with prior studies (e.g. Sufi (2007)). For example, the mean/median loan amount is $343/$135 million, the mean loan maturity is 3.6 years, and the mean all-in-drawn spread is 220 basis points. Panel D reports borrower characteristics. The mean/median book value of assets is $4,470/$884 million. 24% of loans are issued by borrowers that have an investment grade rating. In 51% of cases, the borrowers do not have a credit rating at all.

[Table 1 here]

Table 2 presents descriptive statistics distinguishing between firms that have CDS trading at some point in time during the sample period and firms that never have actively traded CDS during the sample period. Panel A reports descriptives for two CDS trading indicators. 46% of the loans issued by CDS firms are issued before CDS inception. Panel B reports descriptives for the syndicate structure indicators. Overall, CDS firms have more diverse syndicates. The mean/median share retained by the lead arranger is 42%/32% for Non-CDS firms and 26%/19% for CDS firms. The median number of lenders is 5 for Non-CDS firms and 12 for CDS firms. Panel C reports loan characteristics. Loans issued by CDS firms are larger with a mean/median size of $980/$600 million compared to the mean/median of $198/$100 million for Non-CDS firms. Also the loan maturity is shorter for CDS firms when compared to Non-CDS firms. Panel D reports borrower characteristics. CDS firms

[10] Potential reporting biases are discussed in Ivashina (2009) and are unlikely to affect our results.

are much larger that Non-CDS firms. The mean/median book value of assets is \$1,624/\$598 million for Non-CDS firms and \$16,985/\$10,488 million for CDS firms. Almost all borrowers, which have CDS trading at some point in time during the sample period, have an S&P rating at the time of the loan issue (97%).

[Table 2 here]

4 Loan Sales, Syndicate Structure, and CDS Trading

4.1 Baseline Specification

We start by establishing a general link between CDS trading, loan sales and syndicate structure. An explicit distinction between *Hypothesis 1* and *Hypothesis 2* is made in Section 5. Figure 1 shows the average loan share retained by the lead bank before and after CDS are actively traded on the borrowers debt.

[Figure 1 here]

We find that the share retained by the lead arranger strongly increases from 21% to 26% after CDS are actively traded on a borrower's debt. This increase is statistically significant at the 1% level. Only the change from year zero (CDS introduction year) to year one is statistically significant, indicating that there is indeed a structural break. This univariate comparison is consistent with *Hypothesis 1* and *Hypothesis 2*, however, other firm characteristics may have changed at the CDS introduction date and firms with actively traded CDS may be different from firms that never have actively traded CDS during our sample period. We follow Ashcraft and Santos (2009) and Subrahmanyam et al. (2014) and address these issues by comparing firms before and after CDS are actively traded on the firm's debt with firms that never have actively traded CDS at any point in time during the sample period, using the following regression framework:

$$\begin{aligned} Syndicate\ Structure_{it} = &\alpha + \beta_1 * CDS\ Traded_i + \beta_2 * CDS\ Trading_{it} \\ &+ X'_{it} * \gamma + \epsilon_{it}. \end{aligned} \tag{1}$$

Syndicate Structure is a syndicate structure indicator. As discussed earlier, we construct three different specifications for this variable, with the main variable being the share of the loan retained by the lead arranger. *CDS Traded* is a dummy that equals one if a firm has actively traded CDS on its debt at any time during the sample period and zero otherwise. *CDS Trading* is a dummy that equals one if a firm has active CDS trading at the time of the loan origination date and zero otherwise. The regression further includes a set of firm and loan characteristics, X. All control variables are defined in detail in the Appendix Table A.I. Also included are time fixed effects, industry fixed effects, and indicator variables for the different loan purposes and loan types. We use OLS to estimate the regressions, however, all results reported in this paper remain qualitatively unchanged if we use a Tobit specification in the models that have *% Held By Lead* or *Herfindahl* as dependend variables.

[Table 3 here]

The results reported in Table 3 provide evidence that banks sell a lower fraction of the loan once credit protection via CDS is available. The share retained by the lead arranger increases by 7 percentage points and the effect is highly statistically significant. This effect is also economically important as compared to the median value of 27%, this change implies an increase in magnitude of about 25%. The effects for *Herfindahl* and *ln(# Lenders)* are similar. Loan syndicates are more concentrated after CDS are traded on a borrower's debt when measured by the Herfindahl index and the number of lenders in the syndicate declines. Again the effects are highly statistically significant.

Turning to the control variables, we find similar effects as Sufi (2007). The lead arranger retains a lower share of the loan if the borrower is larger, if the loan is larger, and if the maturity is longer. This evidence is consistent with the idea that larger firms are less opaque, therefore moral hazard and adverse selection problems are lower in loans to these borrowers, hence the lead arranger can sell a larger fraction of the loan. We further find that lead arrangers retain larger shares in secured loans.

One potential concern is that borrowers may switch to different banks after CDS are traded on a borrower's debt. If banks have different risk attitudes, then the effect reported in Table 3 could be driven by borrowers who switch to banks that hold larger shares in all loans in their portfolios. We address this issue by including bank fixed effects in the regressions. The results are reported in Table 4.

[Table 4 here]

While the effects are economically weaker, they remain statistically highly significant, indicating that the change in syndicate structure after CDS are traded on a borrower's debt cannot be explained by variations across banks.

4.2 Endogeneity

Another concern is that the selection of firms for CDS trading and the timing of CDS inception may be endogenous. Unobserved differences between CDS firms and non-CDS firms could influence both CDS inception and the structure of loan syndicates. We follow Ashcraft and Santos (2009), Subrahmanyam et al.

(2014), and Saretto and Tookes (2013) and address this issue by constructing a model to predict CDS trading for individual firms. As in Subrahmanyam et al. (2014) and Saretto and Tookes (2013) we use *Lender FX Usage* as an instrument for *CDS Trading*. *Lender FX Usage* is constructed at the firm level for each year as the average amount of foreign exchange derivatives held by all the lead arrangers that lend money to the company in the previous five years as a fraction of the total loans of the lead arrangers.[11] Minton et al. (2008) show that banks that use foreign exchange derivatives are more likely to be net buyers of CDSs, hence *Lender FX Usage* is correlated with investors demand for CDS. As foreign exchange hedges are macro hedges, it is unlikely that this variable is directly related to the loan (and borrower) specific syndicate structure.

The economic intuition for using *Lender FX Usage* as an instrument for *CDS Trading* is that market participants that are overall more "derivative-affine" also have a higher demand for credit protection via CDS. Ideally one would like to use both bond and loan market information to determine investors demand for CDS. However, as argued by Saretto and Tookes (2013) the hedging activity of firms' lead banks is expected to impact both the loan and bond components of firms' debt. Lead lenders are also likely to underwrite and hold firms' bonds. Yasuda (2005) shows that lead arrangers of a firm are also likely to be chosen as the bond underwriters. Goldstein and Hotchkiss (2007) find that lead underwriters also tend to hold significant fractions in the bonds.

We use the model to predict CDS trading for each company in each year to employ an instrumental variable estimation. Thereby, the probability of CDS trading as predicted by the first stage is used as an instrument for CDS trading in the second stage. Table 5 reports the results of the instrumental variable estimation. Column 1 reports the model that is used to predict CDS

[11] As in Saretto and Tookes (2013) we use the foreign exchange derivatives used for hedging (not trading) purposes.

trading. The results are similar to Subrahmanyam et al. (2014) and Saretto and Tookes (2013). *Lender FX Usage* is significantly positively related to *CDS Trading* confirming the validity of the inclusion restriction. The second stage results show that, the effect of CDS trading on the share retained by the lead arranger remains highly significant after addressing the endogeneity of CDS inception.[12]

[Table 5 here]

4.3 CDS Market Liquidity

Duffee and Zhou (2001) theoretically show that CDS can replace loan sales as CDS are a flexible way to temporarily lay off credit risk. However, the flexibility of CDS is likely to be determined by the liquidity in the CDS market. If the CDS that are traded on the borrowers debt are illiquid, CDS trading is unlikely to have an effect on loan sales and general syndicate structure. We address this issue and use the borrowers CDS bid-ask spread in the month before the loan origination as a proxy for the liquidity. We divide *CDS Trading* intro three subsets: *CDS Trading*Low Liquidity*, *CDS Trading*Medium Liquidity*, and *CDS Trading*High Liquidity*. Low, medium, and high liquidity are indicator variables for three CDS bid-ask spreads quantiles. The results reported in Table 6 show that CDS trading does only have an effect on syndicate structure if the liquidity is sufficiently high. The coefficients *CDS Trading*Low Liquidity* and *CDS Trading*High Liquidity* are significantly difference from each other at the 1% level in all reported regression. The lead arranger especially sells a lower fraction of the loan if CDS liquidity is high, i.e. the bid-ask spread is low. Also the syndicate concentration and the number of lenders is predominantly affected by trading of liquid CDS contracts.

[12] The results for the other syndicate structure indicators are qualitatively similar but not reported to save space. The results are available from the author upon request.

[Table 6 here]

5 CDS Trading, Monitoring, and Moral Hazard

The evidence so far is consistent with both *Hypothesis 1* and *Hypothesis 2*. Lead arrangers may sell a lower fraction of the loan because loan sales are (partially) replaced by CDS. Alternatively, lead arrangers may sell a lower fraction of the loan because investors are less willing to invest in syndicated loans if the lender can no longer credible commit to monitor the borrower. We disentangle the effects empirically by analyzing different types of borrowers and lenders. If the moral hazard effect (the lead arranger can no longer credibly commit to monitor the borrower if anonymous hedging via CDS is possible) is the dominant effect, then this problem should be especially severe for borrowers that require extensive monitoring. Therefore, we analyze if the effect of CDS trading on the share retained by the lead arranger is especially pronounced for more risky borrowers, and more opaque borrowers. We use leverage and interest coverage as proxies for borrower risk. We further use the number of analysts covering the firm as firms with higher analyst coverage are typically less opaque. Results are reported in Table 7.

[Table 7 here]

The results show that the effect of CDS trading on the share retained by the lead arranger does not differ between borrowers with different required monitoring intensities, which is unsupportive of *Hypothesis 2*. The fraction of the loan sold by the lead arranger is, if anything, larger for more opaque borrowers. The effect however, is only statistically significant at the 10% level.

Sufi (2007) argues that previous lending relationships between the borrower and the lead arranger can serve as a measure of the information advantage of the lead arranger with respect to participant lenders. Moral hazard should be less severe if a lending relationship exists because the lead arranger has already put in the effort required to learn about the firm. We therefore test if the effect of CDS trading on the share retained by the lead arranger is more severe if the lead arranger and the borrower do not have a previous lending relationship. Following Bharath, Dahiya, Saunders, and Srinivasan (2011), we construct a dummy variable, *Rel(Dummy)*, which equals one if the firm borrowed from the same lead lender in the previous five years and zero otherwise and interact this variable with *CDS Trading*. Results reported in Table 7 show that the effect of *CDS Trading* on *% Held By Lead* is not significantly different for relationship loans. The lead arranger sells, if anything, a larger fraction of the loan if no prior lending relationship exists. This is again unsupportive of *Hypothesis 2*. The general effect of *Rel(Dummy)* is significantly negative, confirming the results of Sufi (2007).

Finally, we test the effect of lender reputation. As shown theoretically by Parlour and Winton (2013), moral hazard problems arising from CDS trading are less severe if the lenders reputation is higher. Following Sufi (2007), we measure lead arranger reputation, *Lead Reputation*, by the market share (by amount) of the lead arranger in the year prior to the loan in question. Results reported in Table 7 show that the effect of *CDS Trading* on *% Held By Lead* is not significantly different for lenders with different reputations. The general effect of *Lead Reputation* is significantly negative, confirming the results of Sufi (2007).[13]

The analysis so far focuses on borrower and lead bank characteristics, however, if CDS trading amplifies moral hazard problems in loan syndicates,

[13] The effect of *CDS Trading* on *Herfindahl* and *ln(# Lenders)* does also not differ between different types of borrowers and lenders (not tabulated to save space).

this should also have an effect on the *overall* syndicate structure. We therefore additionally analyze which banks end up as syndicate members and whether the syndicate participant selection process is different after CDS are actively traded on the borrowers debt. The main argument is that the degree of information asymmetry between a potential participant and the lead bank is not the same for all potential syndicate participants. Therefore also moral hazard problems will be more severe for some banks compared to others. For example, a bank that already knows the borrower from previous deals is less dependent on the information generation and monitoring by the lead arranger. Hence, this bank may decide to participate in a syndicate even if CDS availability prevents the lead arranger from credibly committing to monitor the borrower.

We follow Sufi (2007) and model the choice of loan syndicate members. For each deal the "potential" participant choice set consists of all financial institutions that are active in the U.S. syndicated loan market in the year of the loan in question.[14] We relate a dummy variable, $Participant_{ij}$, which equals one if bank j participated in loan i and zero otherwise, to proxies for the degree of information asymmetry between bank j and the lead arranger of deal i. We use three different measures for information asymmetry: (i) *Former Deal With Borrower* is a dummy variable, which equals one if bank j is a former lender of the borrowing firm, and zero otherwise. (ii) *Same Region As Borrower* is a dummy variable, which equals one if bank j is in the same region as the borrowing firm, and zero otherwise. (iii) *Former Deal With Lead Arranger* is a dummy variable, which equals one if bank j has made a deal in the past where the lead arranger of loan i was also involved, and zero otherwise. We exclude all lead arrangers from the estimation and restrict our sample to firms that have actively traded CDS on their debt at any point in time during the sample period to compare the same set of firms before and

[14] Sufi (2007) focuses on banks with a market share of at least 0.5%. Imposing this additional restriction does not affect our results.

after CDS are actively traded. We include deal fixed effects as we are interested in the variation across potential participants *within* deals.[15] We use a linear probability specification beacause of the large number of fixed effects. We use the following regression framework:

$$Participant_{ij} = \alpha_i + \beta_1 * Bank_{ji} + \beta_2 * Bank_{ji} * CDS\ Trading_i + \epsilon_{ij}, \quad (2)$$

where $Bank_{ji}$ is a proxy for the degree of information asymmetry between bank j and the lead arranger of deal i. As described above, we use three different proxies. We are particularly interested in how the effect of $Bank_{ji}$ on $Participant_{ij}$ varies with CDS availability (captured by β_2).[16] If CDS trading amplifies moral hazard problems, primarily banks that are less dependent on the information generation and monitoring by the lead arranger should remain in the syndicate.

[Table 8 here]

The results presented in Table 8 show — consistent with Sufi (2007) — that banks that already know the borrower from prior deals and banks that are located in the same region as the borrower are significantly more likely to end up as syndicate members compared to other banks.[17] Further, also banks that already know the lead arranger from prior deals are more likely to participate in a syndicate compared to other banks. However, the results also show that the syndicate participant selection process is not significantly different for loans in which CDS are actively traded on the borrowers debt. These results are inconsistent with *Hypothesis 2*. If anything, column (4) suggests that the effect of *Former Deal With Lead Arranger* on *Participant* is

[15] Our results remain virtually unchanged if we include deal and borrower characteristics as in Sufi (2007) instead of deal fixed effects.
[16] Note that *CDS Trading* is omitted because of the deal fixed effects.
[17] Note that the number of observations is lower in column (2) and column (4) because Dealscan does not provide the exact location (country and state) for all companies.

weaker if CDS are available. This is consistent with the conjecture that CDS availability attracts new investors.

Overall, the results reported in this section show that an increase in moral hazard is unlikely to be the dominant effect on the fraction of a loan sold by the lead arranger.

6 Robustness

6.1 CDS Introduction Dates

One potential problem is that exact CDS introduction dates are hard to identify and several data sources containing CDS spreads are available. Since CDS are not traded on centralized exchanges, not all databases necessarily contain the exact same information. For robustness purposes, we use all CDS spreads from the CMA Datavision database to identify CDS introduction dates and additionally report the baseline regressions using this database. Results are reported in Table 9.

[Table 9 here]

The results using CMA data to identify CDS introduction dates are similar to those using Bloomberg data. Again, all syndicate structure indicators show that lenders form a more concentrated syndicate after CDS are available on a borrower's debt. Also the magnitudes are comparable to the results reported in Table 3.[18]

6.2 Secondary Market Trading

Another potential concern is that an increasing number of loans are traded in the secondary market. It could be that the availability of credit protec-

[18] Also combining CMA and Bloomberg data yields similar results.

tion via CDS also increases the likelihood of secondary market trading. The lead arranger may initially agree to retain a larger fraction of the loan but immediately sell the loan after the origination. Unfortunately, Dealscan only provides loan information as of origination so one cannot track the syndicate composition over time. However, Ivashina and Sun (2011) show (using a hand collected sample of loan amendments) that lead arrangers almost never sell their stakes in the loan.

We additionally address this issue by excluding all companies from the sample that issued loans that are traded on the secondary market during the sample period.[19] The results remain qualitatively unchanged.[20]

7 Conclusion

This study provides empirical evidence on how credit derivative trading affects loan sales and the structure of loan syndicates. Using CDS trading data and a large sample of syndicated loans issued between 2000 to 2010, we show that lenders sell significantly lower fractions of loans once credit protection via CDS is possible. Further, the syndicate concentration (measured by the Herfindahl index) increases, and the number of lenders in the syndicate declines. These effects are stronger if CDS liquidity is higher and the results are robust to controlling for the potential endogeneity of CDS introduction. The reduction in loan sales and the increase in syndicate concentration is consistent with diversification benefits of the CDS market, which reduces the need for risk-sharing via syndication.

However, a reduction in loan sales after CDS introduction is also consistent with Parlour and Winton (2013), who show theoretically that lenders can

[19] We classify traded loans as loans that have a Loan Identification Number (LIN). The LIN is the main identifier in secondary loan market databases. E.g. Drucker and Puri (2009) use the LIN to merge Dealscan with the Loan Syndications and Trading Association (LSTA) Mark-to-Market Pricing database.

[20] The results are not reported to save space but available from the author upon request.

no longer credible commit to monitor a borrower if laying off credit risk anonymously via CDS is possible. Without a credible signal by the lead arranger, investors willingness to participate in a syndicate declines. Disentangling the risk management from the moral hazard effect empirically, we find that potentially negative effects of CDS trading are of minor importance in the syndicated loan market.

This study helps to understand the impact of CDS trading on the nature and operation of credit markets. Though the importance of credit derivatives has grown enormously in recent years, these effects are not fully understood. We provide evidence that is consistent with CDS being a flexible risk management tool that (partially) replaces loan sales and the need for a diverse syndicate structure.

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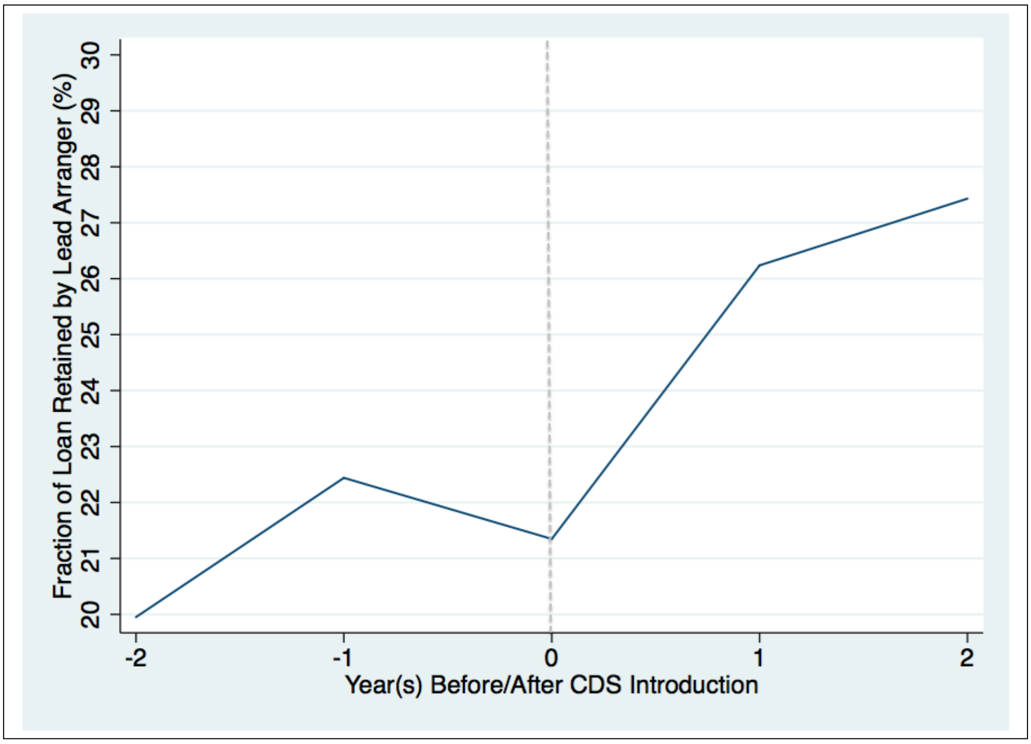
Appendix

A.1 Figures

Figure 1: Loan Share Retained by Lead Bank: Before vs. After CDS Introduction

This figures shows the average loan share retained by the lead bank before and after CDS are actively traded on the borrowers debt ([-2,+2] years surrounding the CDS introduction).



A.2 Tables

Table 1: Descriptive Statistics

This table reports summary statistics for CDS trading indicators, syndicate structure indicators, loan characteristics and borrower characteristics. All variables are defined in the Appendix Table A.I.

	mean	p25	p50	p75	sd	count
Panel A: CDS Trading Indicators						
CDS Traded (0/1)	0.19	0.00	0.00	0.00	0.39	13744
CDS Trading (0/1)	0.09	0.00	0.00	0.00	0.28	13744
Panel B: Syndicate Structure Indicators						
% Held by Lead Arranger	38.15	17.50	28.00	50.00	27.92	3842
Sole Lender (0/1)	0.18	0.00	0.00	0.00	0.39	13744
# Lenders	7.73	2.00	5.00	10.00	8.12	13744
Herfindahl	2676.67	863.68	1561.63	3422.22	2701.12	3426
Panel C: Loan Characteristics						
Facility Amount (million USD)	342.45	40.00	132.05	350.00	815.61	13744
Maturity (Months)	44.05	24.00	48.00	60.00	23.09	13744
Secured (0/1)	0.56	0.00	1.00	1.00	0.50	13744
All In Spread Drawn (bp)	220.03	100.00	200.00	300.00	159.74	13744
Panel D: Borrower Characteristics						
Total Assets (million USD)	4469.83	259.60	874.08	2937.25	10985.77	13744
Leverage	0.30	0.13	0.27	0.41	0.24	13744
Coverage	17.68	2.64	5.40	12.29	49.90	13744
Profitability	0.14	0.07	0.13	0.21	0.20	13744
Tangibility	0.34	0.14	0.28	0.51	0.24	13744
Current Ratio	1.77	1.05	1.50	2.16	1.13	13744
Market-To-Book	1.66	1.09	1.36	1.86	0.96	13744
Investment Grade (0/1)	0.24	0.00	0.00	0.00	0.43	13744
Not Rated (0/1)	0.50	0.00	1.00	1.00	0.50	13744

Table 2: Descriptive Statistics: No CDS Traded vs. CDS Traded

This table reports descriptive statistics for CDS trading indicators, syndicate structure indicators, loan characteristics and borrower characteristics. **CDS Traded** indicates that the borrower has actively traded CDS on its debt at any point in time during the sample period. All variables are defined in the Appendix Table A.I.

	CDS Traded = 0				**CDS Traded = 1**			
	mean	p50	sd	count	mean	p50	sd	count
Panel A: CDS Trading Indicators								
CDS Traded (0/1)	0.00	0.00	0.00	11190	1.00	1.00	0.00	2554
CDS Trading (0/1)	0.00	0.00	0.00	11190	0.47	0.00	0.50	2554
Panel B: Syndicate Structure Indicators								
% Held by Lead Arranger	42.00	32.00	28.79	2937	25.62	18.83	20.40	905
Sole Lender (0/1)	0.22	0.00	0.41	11190	0.03	0.00	0.16	2554
# Lenders	6.34	5.00	7.09	11190	13.83	12.00	9.44	2554
Herfindahl	3126.84	2008.89	2830.33	2635	1177.04	750.00	1412.33	791
Panel C: Loan Characteristics								
Facility Amount (million USD)	196.42	100.00	350.96	11190	982.25	600.00	1593.16	2554
Maturity (Months)	45.36	48.00	22.69	11190	38.30	36.00	23.94	2554
Secured (0/1)	0.64	1.00	0.48	11190	0.20	0.00	0.40	2554
All In Spread Drawn (bp)	243.30	225.00	158.18	11190	118.09	70.00	122.21	2554
Panel D: Borrower Characteristics								
Total Assets (million USD)	1617.26	586.26	4549.87	11190	16968.01	10488.25	19157.49	2554
Leverage	0.30	0.26	0.26	11190	0.31	0.30	0.16	2554
Coverage	19.43	5.18	54.79	11190	10.00	6.22	13.14	2554
Profitability	0.13	0.12	0.21	11190	0.20	0.17	0.14	2554
Tangibility	0.32	0.25	0.24	11190	0.41	0.40	0.22	2554
Current Ratio	1.86	1.59	1.20	11190	1.34	1.21	0.62	2554
Market-To-Book	1.65	1.36	0.98	11190	1.67	1.39	0.86	2554
Investment Grade (0/1)	0.11	0.00	0.32	11190	0.77	1.00	0.42	2554
Not Rated (0/1)	0.61	1.00	0.49	11190	0.03	0.00	0.18	2554

Table 3: The Impact of CDS Trading on the Structure of Loan Syndicates

This table reports difference-in-differences OLS regression results analyzing the impact of CDS trading on the structure of loan syndicates. The dependent variables are syndicate structure indicators: the percentage of the loan held by the lead arranger, the Herfindahl-index for the syndicate concentration, and the number of lenders. The key independent variable is *CDS Trading*, a dummy variable, which equals one if CDS are actively traded on the borrower's debt at the time of the loan origination, and zero otherwise. *CDS Traded* is a dummy variable, which equals one if CDS are traded on the borrower's debt at any point of time during the sample period, and zero otherwise. All variables are defined in the Appendix Table A.I. Standard errors are heteroskedasticity robust and clustered at the firm level to account for non-independent observations within firms. *,**,*** Indicate statistical significance at the 10%,5%,1% level.

	(1) % Held By Lead	(2) % Held By Lead	(3) Herfindahl	(4) Herfindahl	(5) ln(# Lenders)	(6) ln(# Lenders)
Panel A: CDS Trading Indicators						
CDS Trading	11.08***	6.70***	1014.89***	551.05***	-0.06*	-0.07**
	(1.57)	(1.61)	(130.40)	(126.91)	(0.03)	(0.04)
CDS Traded		7.76***		813.33***		0.02
		(1.47)		(131.62)		(0.03)
Panel B: Loan Characteristics						
ln(Facility Amount)	-8.66***	-8.66***	-1021.63***	-1020.17***	0.22***	0.22***
	(0.58)	(0.58)	(60.84)	(60.56)	(0.01)	(0.01)
ln(Maturity)	-5.30***	-5.29***	-576.35***	-574.94***	0.14***	0.14***
	(0.78)	(0.78)	(68.57)	(67.79)	(0.01)	(0.01)
Secured	4.44***	4.31***	341.75***	323.34***	-0.01	-0.01
	(1.11)	(1.09)	(95.90)	(94.48)	(0.02)	(0.02)
Panel C: Borrower Characteristics						
ln(Total Assets)	-2.79***	-3.43***	-336.99***	-403.91***	0.11***	0.11***
	(0.59)	(0.61)	(59.10)	(60.36)	(0.01)	(0.01)
Leverage	-2.87	-3.42	-474.93*	-523.15*	0.00	0.00
	(3.36)	(3.38)	(275.27)	(273.71)	(0.04)	(0.04)
Coverage	0.01	0.01	0.86	0.88	-0.00**	-0.00**
	(0.01)	(0.01)	(0.91)	(0.90)	(0.00)	(0.00)
Profitability	-4.65	-4.21	-636.40**	-594.80**	0.09**	0.09**
	(2.87)	(2.83)	(267.23)	(262.98)	(0.04)	(0.04)
Tangibility	-1.98	-1.93	-139.94	-135.07	-0.10***	-0.10***
	(2.74)	(2.75)	(241.96)	(242.15)	(0.04)	(0.04)
Current Ratio	0.41	0.45	22.18	27.02	-0.02***	-0.02***
	(0.54)	(0.54)	(47.92)	(47.45)	(0.01)	(0.01)
Market-To-Book	-0.67	-0.68	-20.67	-22.49	0.01*	0.01*
	(0.48)	(0.47)	(44.18)	(44.16)	(0.01)	(0.01)
Investment Grade	0.60	-0.71	328.15**	187.35	0.04	0.03
	(1.65)	(1.61)	(144.79)	(142.86)	(0.03)	(0.03)
Not Rated	-1.95	-1.96	14.18	10.90	-0.06**	-0.06**
	(1.70)	(1.70)	(144.71)	(143.99)	(0.02)	(0.02)
Intercept	254.82***	260.28***	26801.07***	27448.73***	-3.25***	-3.24***
	(15.56)	(15.64)	(1088.65)	(1123.61)	(0.15)	(0.15)
Obs.	3842	3842	3426	3426	13744	13744
Adj. R^2	0.377	0.382	0.515	0.521	0.520	0.520
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Loan Purpose Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Loan Type Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 4: The Impact of CDS Trading on the Structure of Loan Syndicates - Controlling for Bank Fixed Effects

This table reports difference-in-differences OLS regression results analyzing the impact of CDS trading on the structure of loan syndicates. The dependent variables are syndicate structure indicators: the percentage of the loan held by the lead arranger, the Herfindahl-index for the syndicate concentration, and the number of lenders. The key independent variable is *CDS Trading*, a dummy variable, which equals one if CDS are actively traded on the borrower's debt at the time of the loan origination, and zero otherwise. *CDS Traded* is a dummy variable, which equals one if CDS are traded on the borrower's debt at any point of time during the sample period, and zero otherwise. All variables are defined in the Appendix Table A.I. Standard errors are heteroskedasticity robust and clustered at the firm level to account for non-independent observations within firms. *,**,*** indicate statistical significance at the 10%,5%,1% level.

	(1) % Held By Lead	(2) % Held By Lead	(3) Herfindahl	(4) Herfindahl	(5) ln(# Lenders)	(6) ln(# Lenders)
Panel A: CDS Trading Indicators						
CDS Trading	7.92***	3.95***	882.20***	436.70***	-0.07**	-0.08**
	(1.38)	(1.43)	(121.52)	(124.02)	(0.03)	(0.04)
CDS Traded		7.35***		812.60***		0.01
		(1.34)		(123.26)		(0.03)
Panel B: Loan Characteristics						
ln(Facility Amount)	-8.66***	-8.66***	-942.53***	-942.50***	0.20***	0.20***
	(0.57)	(0.57)	(58.78)	(58.75)	(0.01)	(0.01)
ln(Maturity)	-5.72***	-5.74***	-549.33***	-550.26***	0.13***	0.13***
	(0.69)	(0.69)	(64.82)	(64.13)	(0.01)	(0.01)
Secured	1.86*	1.71*	152.73	131.29	0.03	0.03
	(1.04)	(1.03)	(97.48)	(96.08)	(0.02)	(0.02)
Panel C: Borrower Characteristics						
ln(Total Assets)	-3.64***	-4.24***	-323.90***	-390.59***	0.10***	0.09***
	(0.56)	(0.57)	(56.59)	(58.30)	(0.01)	(0.01)
Leverage	-6.87**	-7.40***	-702.79***	-749.31***	0.02	0.01
	(2.74)	(2.75)	(247.43)	(246.80)	(0.04)	(0.04)
Coverage	0.01	0.01	0.39	0.42	-0.00**	-0.00**
	(0.01)	(0.01)	(0.89)	(0.88)	(0.00)	(0.00)
Profitability	-1.81	-1.45	-289.64	-248.36	0.05	0.05
	(3.05)	(3.01)	(293.74)	(289.04)	(0.04)	(0.04)
Tangibility	-1.51	-1.40	-120.37	-111.33	-0.06	-0.06
	(2.38)	(2.38)	(225.93)	(226.18)	(0.04)	(0.04)
Current Ratio	0.10	0.13	7.60	12.28	-0.02**	-0.02**
	(0.48)	(0.48)	(46.00)	(45.76)	(0.01)	(0.01)
Market-To-Book	-0.69	-0.72	-21.40	-25.46	0.01*	0.01*
	(0.47)	(0.47)	(43.85)	(43.75)	(0.01)	(0.01)
Investment Grade	0.12	-1.11	254.12*	118.41	0.02	0.02
	(1.52)	(1.47)	(140.89)	(137.25)	(0.03)	(0.03)
Not Rated	-1.34	-1.35	-7.26	-9.45	-0.05**	-0.05**
	(1.48)	(1.48)	(137.86)	(137.22)	(0.02)	(0.02)
Intercept	236.56***	241.99***	25075.71***	25827.42***	-2.90***	-2.89***
	(14.06)	(14.17)	(1272.54)	(1313.80)	(0.13)	(0.13)
Obs.	3842	3842	3426	3426	13744	13744
Adj. R^2	0.508	0.512	0.565	0.571	0.559	0.559
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Loan Purpose Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Loan Type Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 5: The Impact of CDS Trading on the Structure of Loan Syndicates - IV-Estimation

This table reports instrumental variable regressions analyzing the impact of CDS trading on the structure of loan syndicates. The instrument for CDS trading is the amount of foreign exchange derivatives held by the lead arranger for hedging purposes (not trading) as a fraction of the total assets of the lead arranger. A logit model is used to obtain the probability of CDS trading for each loan (column 1). The predicted probability is used as the instrumental variable in the models reported in column 2 and column 3. The dependent variable in the models reported in column 2 and column 3 is the percentage of the loan held by the lead arranger. All variables are defined in the Appendix Table A.I. Standard errors are heteroskedasticity robust and clustered at the firm level to account for non-independent observations within firms. *,**,*** Indicate statistical significance at the 10%,5%,1% level.

	(1) CDS Trading	(2) % Held By Lead	(3) % Held By Lead
Panel A: CDS Trading Indicators			
Instrumented CDS Trading		25.30***	18.30***
		(5.02)	(5.09)
CDS Traded			8.38***
			(1.50)
Panel B: Loan Characteristics			
ln(Facility Amount)		-8.18***	-8.18***
		(0.65)	(0.64)
ln(Maturity)		-5.28***	-5.34***
		(0.88)	(0.86)
Secured		3.83***	3.79***
		(1.18)	(1.16)
Panel C: Borrower Characteristics			
ln(Total Assets)	0.37***	-2.32***	-3.21***
	(0.03)	(0.71)	(0.72)
Leverage	0.04	-3.67	-4.74
	(0.08)	(3.44)	(3.43)
Coverage	-0.00	0.01	0.01
	(0.00)	(0.01)	(0.01)
Profitability	0.30	-0.90	-0.22
	(0.18)	(3.46)	(3.39)
Tangibility	0.00	-0.07	0.25
	(0.17)	(2.88)	(2.89)
Current Ratio	-0.07**	1.30**	1.28**
	(0.03)	(0.63)	(0.62)
Market-To-Book	0.10***	-1.62***	-1.43***
	(0.02)	(0.56)	(0.54)
Investment Grade	0.44***	-2.31	-3.21*
	(0.08)	(1.82)	(1.73)
Not Rated	-0.52***	-2.02	-2.49
	(0.08)	(1.72)	(1.71)
Panel D: Lender Characteristics			
Lender FX Usage	0.30**		
	(0.13)		
Obs.	28404	3106	3106
Adj. R^2		0.314	0.323
Pseudo R^2	0.382		
Time Fixed Effects	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes
Loan Purpose Fixed Effects		Yes	Yes
Loan Type Fixed Effects		Yes	Yes

Table 6: The Impact of CDS Trading on the Structure of Loan Syndicates - CDS Market Liquidity

This table reports difference-in-differences OLS regression results analyzing the impact of CDS trading on the structure of loan syndicates. The dependent variables are syndicate structure indicators: the percentage of the loan held by the lead arranger, the Herfindahl-index for the syndicate concentration, and the number of lenders. The key independent variables are *CDS Trading*Low Liquidity*, *CDS Trading*Medium Liquidity* and *CDS Trading*High Liquidity*. *CDS Trading* is a dummy variable which equals one if CDS are actively traded on the borrower's debt at the time of the loan origination, and zero otherwise. *Low Liquidity/Medium Liquidity/High Liquidity* is a dummy variable which equals one if the borrower's CDS bid-ask spread is in the low/medium/high quantile in the month prior to the loan issue and zero otherwise. *CDS Traded* is a dummy variable, which equals one if CDS are traded on the borrower's debt at any point of time during the sample period, and zero otherwise. All variables are defined in the Appendix Table A.I. Standard errors are heteroskedasticity robust and clustered at the firm level to account for non-independent observations within firms. *,**,*** indicate statistical significance at the 10%,5%,1% level.

	(1) % Held By Lead	(2) Herfindahl	(3) ln(# Lenders)
CDS Trading*Low Liquidity	3.36	181.46	0.00
	(2.37)	(186.88)	(0.04)
CDS Trading*Medium Liquidity	7.16***	549.20***	-0.00
	(2.35)	(182.80)	(0.05)
CDS Trading*High Liquidity	10.08***	959.25***	-0.22***
	(2.01)	(153.27)	(0.05)
CDS Traded	7.90***	832.46***	0.01
	(1.47)	(130.98)	(0.03)
Obs.	3836	3420	13729
Adj. R^2	0.382	0.522	0.521
Time Fixed Effects	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes
Loan Purpose Fixed Effects	Yes	Yes	Yes
Loan Type Fixed Effects	Yes	Yes	Yes
hascontr	Yes	Yes	Yes

Table 7: CDS Trading, Monitoring, and Moral Hazard

This table reports difference-in-differences OLS regression results analyzing the impact of CDS trading on the structure of loan syndicates distinguishing between different types of borrowers and lenders. The dependent variable is the percentage of the loan held by the lead arranger. The key independent variables is *CDS Trading*, a dummy variable, which equals one if CDS are actively traded on the borrower's debt at the time of the loan origination, and zero otherwise *CDS Traded* is a dummy variable, which equals one if CDS are traded on the borrower's debt at any point of time during the sample period, and zero otherwise. *Leverage* is the ratio of book value of total debt to book value of assets. *Coverage* is the ratio of EBITDA to interest expenses. *# Analysts* is the number of analysts covering the borrower at the time of the loan origination. *Rel(Dummy)* is a dummy variable which equals one if the firm borrowed from the same lead lender in the previous five years and zero otherwise. *Lead Reputation* is the market share (by amount) of the lead arranger in the year prior to the loan in question. All items are defined in the Appendix Table A.I. Standard errors are heteroskedasticity robust and clustered at the firm level to account for non-independent observations within firms. *,**,*** indicate statistical significance at the 10%,5%,1% level.

	(1) % Held By Lead	(2) % Held By Lead	(3) % Held By Lead	(4) % Held By Lead	(5) % Held By Lead
CDS Trading	3.09***	0.85	0.47	2.70*	2.73***
	(1.01)	(0.54)	(0.76)	(1.61)	(0.94)
CDS Trading*Leverage	-6.55**				
	(2.77)				
CDS Trading*Coverage		0.04			
		(0.03)			
CDS Trading*# Analysts			0.07		
			(0.05)		
CDS Trading*Rel(Dummy)				-1.68	
				(1.60)	
CDS Trading*Lead Reputation					-11.34*
					(6.63)
Leverage	1.13	0.94	0.74	1.05	0.92
	(1.66)	(1.62)	(1.62)	(1.62)	(1.62)
Coverage	0.01	0.01	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
# Analysts			-0.07***		
			(0.03)		
Rel(Dummy)				-0.79	
				(0.55)	
Lead Reputation					-1.18
					(3.69)
CDS Traded	-0.95*	-0.94*	-0.72	-0.98*	-0.88*
	(0.52)	(0.52)	(0.52)	(0.52)	(0.53)
Obs.	3842	3842	3842	3842	3704
Adj. R^2	0.191	0.190	0.191	0.191	0.196
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
Loan Purpose Fixed Effects	Yes	Yes	Yes	Yes	Yes
Loan Type Fixed Effects	Yes	Yes	Yes	Yes	Yes
Controls For Borrower Characteristics	Yes	Yes	Yes	Yes	Yes
Controls For Loan Characteristics	Yes	Yes	Yes	Yes	Yes

Table 8: Participant Choice Estimation

This table presents coefficient estimates for a linear probability specification estimating how bank characteristics affect the probability of being chosen as a participant in a syndicated loan. Estimations include deal fixed effects. The choice set includes all banks that are active in the syndicated loan market in the year of the loan. Firms that never have actively traded CDS on their debt during the sample period are excluded. *CDS Trading* is a dummy variable, which equals one if CDS are actively traded on the borrower's debt at the time of the loan origination, and zero otherwise. *Former Deal With Borrower* is a dummy variable, which equals one if the bank is a former lender of the borrowing firm, and zero otherwise. *Same Region As Borrower* is a dummy variable, which equals one if the bank is in the same region as the borrowing firm, and zero otherwise. *Former Deal With Lead Arranger* is a dummy variable, which equals one if the bank has made a deal in the past where the current lead arranger was also involved, and zero otherwise. All items are defined in the Appendix Table A.I. Standard errors are heteroskedasticity robust and clustered at the firm level to account for non-independent observations within firms. *,**,*** indicate statistical significance at the 10%,5%,1% level.

	(1) Participant	(2) Participant	(3) Participant	(4) Participant
Former Deal With Borrower	0.287***			0.300***
	(0.016)			(0.013)
Former Deal With Borrower*CDS Trading	0.021			0.015
	(0.018)			(0.015)
Same Region As Borrower		0.017***		0.008***
		(0.003)		(0.002)
Same Region As Borrower*CDS Trading		-0.001		-0.001
		(0.003)		(0.003)
Former Deal With Lead Arranger			0.016***	0.008***
			(0.001)	(0.000)
Former Deal With Lead Arranger*CDS Trading			-0.000	-0.004***
			(0.001)	(0.001)
Intercept	0.003***	0.016***	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Obs.	3,082,122	1,712,577	3,082,122	1,712,577
Adj. R^2	0.217	0.008	0.011	0.232
Deal Fixed Effects	Yes	Yes	Yes	Yes

Table 9: Robustness: CDS Trading - CMA Data

This table reports difference-in-differences OLS regression results analyzing the impact of CDS trading on the structure of loan syndicates. The difference to Table 2 is that data from CMA instead of Bloomberg data is used to identify which borrowers have actively traded CDS on their debt. The dependent variables are syndicate structure indicators: the percentage of the loan held by the lead arranger, the Herfindahl-index for the syndicate concentration, and the number of lenders. The key independent variable is *CDS Trading*, a dummy variable, which equals one if CDS are actively traded on the borrower's debt at the time of the loan origination, and zero otherwise. *CDS Traded* is a dummy variable, which equals one if CDS are traded on the borrower's debt at any point of time during the sample period, and zero otherwise. All items are defined in the Appendix Table A.I. Standard errors are heteroskedasticity robust and clustered at the firm level to account for non-independent observations within firms. *,**,*** indicate statistical significance at the 10%,5%,1% level.

	(1) % Held By Lead	(2) Herfindahl	(3) ln(# Lenders)
Panel A: CDS Trading Indicators			
CDS Traded	6.44***	807.75***	0.07**
	(1.48)	(127.42)	(0.03)
CDS Trading	6.60***	416.85***	-0.16***
	(1.60)	(135.50)	(0.04)
Panel B: Loan Characteristics			
ln(Facility Amount)	-8.46***	-999.58***	0.22***
	(0.57)	(59.68)	(0.01)
ln(Maturity)	-5.58***	-593.31***	0.15***
	(0.76)	(65.53)	(0.01)
Secured	4.63***	350.00***	-0.02
	(1.08)	(93.41)	(0.02)
Panel C: Borrower Characteristics			
ln(Total Assets)	-3.16***	-379.08***	0.10***
	(0.59)	(58.79)	(0.01)
Leverage	-3.39	-574.56**	0.00
	(3.34)	(272.41)	(0.04)
Coverage	0.01	0.71	-0.00**
	(0.01)	(0.90)	(0.00)
Profitability	-4.02	-569.96**	0.10***
	(2.81)	(261.95)	(0.04)
Tangibility	-2.33	-163.85	-0.10***
	(2.70)	(238.93)	(0.04)
Current Ratio	0.50	25.38	-0.02***
	(0.53)	(46.87)	(0.01)
Market-To-Book	-0.52	-13.28	0.01
	(0.47)	(43.34)	(0.01)
Investment Grade	0.58	204.90	0.03
	(1.55)	(134.88)	(0.03)
Not Rated	-0.93	60.49	-0.07***
	(1.67)	(141.68)	(0.02)
Intercept	240.38***	26747.35***	-3.42***
	(13.92)	(1105.22)	(0.16)
Obs.	4020	3586	14339
Adj. R^2	0.381	0.519	0.520
Time Fixed Effects	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes
Loan Purpose Fixed Effects	Yes	Yes	Yes
Loan Type Fixed Effects	Yes	Yes	Yes

A.3 Variable Definitions

Table A.I: Variable Definitions

Variable Name	Definition	Source
CDS Trading Indicators:		
CDS Trading	A dummy variable, which equals one if CDS are actively traded on the borrower's debt at the time of the loan origination, and zero otherwise.	Bloomberg & CMA
CDS Traded	A dummy variable, which equals one if CDS are traded on the borrower's debt at any point of time during the sample period, and zero otherwise.	Bloomberg & CMA
Low Liquidity	A dummy variable which equals one if the borrower's CDS bid-ask spread is in the high quantile in the month prior to the loan issue and zero otherwise.	Bloomberg
Medium Liquidity	A dummy variable which equals one if the borrower's CDS bid-ask spread is in the medium quantile in the month prior to the loan issue and zero otherwise.	Bloomberg
High Liquidity	A dummy variable which equals one if the borrower's CDS bid-ask spread is in the low quantile in the month prior to the loan issue and zero otherwise.	Bloomberg
Syndicate Structure Indicators:		
% Held by Lead Arranger	The share of the loan retained by the lead arranger in %.	Dealscan

Continued on next page

Table A.I – continued from previous page

Variable Name	Definition	Source
Herfindahl	The Herfindahl-Index for the syndicate concentration measured as the sum of the squared shares retained by the different lenders in a loan.	Dealscan
# Lenders	The number of distinct lenders in a loan contract.	Dealscan
Borrower/Issuer characteristics:		
Total Assets	Firm's total assets in $million.	Compustat
Leverage	Long-term debt divided by total assets.	Compustat
Market-to-Book	Market value of the firm divided by the book value of assets.	Compustat
Tangibility	Net property plant and equipment divided by total assets.	Compustat
Coverage	Interest expenses divided by EBITDA.	Compustat
Profitability	EBITDA divided by total assets.	Compustat
Current Ratio	Current assets divided by current liabilities.	Compustat
Not Rated	A dummy variable, which equals one if the borrower was not rated by S&P at the time of the debt issue.	Compustat
Investment Grade	A dummy variable, which equals one if the borrower was rated BBB- or better by S&P at the time of the debt issue.	Compustat
# Analysts	The number of analysts covering the borrower at the time of the loan origination.	I/B/E/S
Loan/Lender characteristics:		

Continued on next page

Table A.I – continued from previous page

Variable Name	Definition	Source
Facility Amount	Overall facility volume in $million.	Dealscan
Maturity	Time to maturity in months.	Dealscan
Secured	A dummy variable, which equals one if the loan is secured and zero otherwise.	Dealscan
Sole Lender	A dummy variable, which equals one if the loan is not syndicated and zero otherwise.	Dealscan
All In Spread Drawn	The facility All In Spread Drawn (bps).	Dealscan
Lender FX Usage	The average amount of foreign exchange derivatives held by all the lead arrangers that lend money to the company in the previous five years as a fraction of the total loans of the lead arrangers.	Call Reports
Lead Reputation	The market share (by amount) of the lead arranger in the year prior to the loan in question.	Dealscan
Rel(Dummy)	A dummy variable which equals one if the firm borrowed from the same lead lender in the previous five years and zero otherwise.	Dealscan
Former Deal With Borrower	A dummy variable, which equals one if the bank is a former lender of the borrowing firm, and zero otherwise.	Dealscan
Same Region As Borrower	A dummy variable, which equals one if the bank is in the same region, i.e. in the same country and in the same state, as the borrowing firm, and zero otherwise.	Dealscan
Former Deal With Lead Arranger	A dummy variable, which equals one if the bank has made a deal in the past where the current lead arranger was also involved, and zero otherwise.	Dealscan

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Table A.I – continued from previous page

Variable Name	**Definition**	**Source**
$Participant_{ij}$	A dummy variable, which equals one if bank j participated in loan i, and zero otherwise.	Dealscan

Managerial Optimism and Debt Contract Design

Tim R. Adam   Valentin Burg   Tobias Scheinert   Daniel Streitz

Abstract:

We examine the impact of managerial optimism on the inclusion of performance-pricing provisions in debt contracts (PSD). Given their upwardly biased expectations about the firm's future cash flow, optimistic managers may view PSD as a relatively cheap form of financing. Indeed, we find that optimistic managers are more likely to issue PSD, and choose contracts with greater risk-compensation than rational managers. Consistent with their biased expectations, firms with optimistic managers perform worse than firms with rational managers after issuing PSD. Our results suggest that behavioral aspects can affect debt contract design.

Keywords: Optimism, Performance-Sensitive Debt, Debt Contracting, Syndicated Loans

JEL-Classification: G02, G30, G31, G32

1 Introduction

The recent literature shows that managerial optimism can have significant effects on a firm's financing strategies. For example, Graham, Harvey, and Puri (2012) and Hackbarth (2008) argue that optimistic managers view external funds as unduly costly, which according to Heaton (2002) and Malmendier, Tate, and Yan (2011) can lead to a preference for issuing debt over equity. In this paper we show that besides a firm's capital structure, managerial optimism can also affect certain debt contract design features such as performance-pricing provisions. These specify that the coupon rate on a loan rises if the borrower's performance deteriorates and falls if the borrower's performance improves.

Manso, Strulovici, and Tchistyi (2010) hypothesize that performance-sensitive debt (PSD) can be used to signal a firm's unobservable information about its credit quality to potential lenders. Lenders, who cannot distinguish between high and low quality firms, offer borrowers a menu of contracts, which includes fixed-rate debt and risk-compensating PSD. High quality firms choose PSD because the initial coupon rate is lower compared to fixed-rate debt. The potential for coupon rate increases in PSD is of little importance as high quality firms do not expect their performance to deteriorate. Low quality firms, on the other hand, will not mimic high quality firms as low quality firms expect their credit qualities to deteriorate in the future, which would trigger coupon rate increases and thus higher borrowing costs compared to straight debt contracts. In the resulting separating equilibrium high quality firms issue PSD, while low quality firms issue straight debt.

We argue that optimistic managers, who persistently overestimate their firms' future expected cash flow, may (irrationally) decide to mimic high quality firms and issue PSD in order to benefit from the relatively low initial coupon rate offered by lenders on PSD. This possibility gives rise to a number of new testable hypotheses, which we evaluate in this paper. First, optimistic managers should exhibit a greater likelihood of using PSD than rational managers as they overestimate their firms' credit quality.[1] Second, extending the Manso et al. (2010) framework to continua of credit qualities and performance-pricing provisions predicts that optimistic managers choose PSD contracts with more risk-compensation, that is, contracts with a higher sensitivity of the coupon rate to performance changes, than rational managers on average. This is because contracts with more risk-compensation offer lower initial coupon rates. Finally, the post-issue performance of PSD-issuing firms led by optimistic managers should be worse than the post-issue performance of PSD-issuing firms led by rational managers.

We examine these hypotheses using a sample of syndicated and non-syndicated loan tranches issued between 1992 and 2010, obtained from the LPC Dealscan database. Asquith, Beatty, and Weber (2005) report that the use of performance-pricing provisions has become widespread since the early 1990s. In Adam and Streitz (2013) 47% of loans reported in Dealscan contain performance-pricing provisions.

The terms managerial optimism and overconfidence have been used inconsistently in the literature. We define managerial optimism to mean that the executive persistently overestimates the firm's future expected cash flow. Of course, future cash flow expectations are not observable. We therefore follow the methodology discussed in Malmendier and Tate (2005a) and classify CEOs as optimistic if they ever hold an option until maturity, which is at

[1] Managers do at times seem to overestimate their firms' credit qualities. In 1990, John Bowen, CFO of Morton International Inc., commented on their recent performance-sensitive debt issue, *"[...] the market was giving us a reduction in basis points on the coupon, and we felt there was no probability of violating the covenants [i.e., the performance-pricing thresholds]."* During the life of this PSD, Morton International Inc. experienced several downgrades, from AA to BBB. *(Investment Dealers' Digest, June 1990)*

least 40% in-the-money at the year-end prior to maturity. The rationale behind this measure is that CEOs who typically have a large fraction of personal wealth tied to their companies and only limited diversification abilities across alternative investments should rationally exercise an option once it is in-the-money and exercisable. Only executives who are extremely confident about their firm's future return would decide not to exercise their stock options in these situations. In addition, we construct the Holder67, Pre-/Post-Optimistic and the optimism variable proposed by Sen and Tumarkin (2009) to test for robustness of our results.

Our results are consistent with the above empirical predictions. Optimistic CEOs are 6% more likely to issue PSD than rational CEOs. This is economically significant given an overall mean of about 50%. Optimistic managers also sell more risk-compensation to lenders than rational managers. Finally, we find that the performance of firms with optimistic managers is more likely to deteriorate after the issuance of PSD compared to firms led by rational managers. This result rules out the possibility that the managers, which we classify as optimistic, possess positive inside information about their company's future performance. If this were true, issuing PSD could be a rational choice driven by different information sets and not by differences in opinions. In fact, our result suggests that the issue of PSD may have been harmful for firms run by optimistic managers.

A potential concern with our analysis is that a firm's choice to hire an optimistic CEO is endogenous. This decision might be correlated with the same variables that also affect the decision to issue PSD. We address this issue in two ways. First, we model the firm's choice to hire an optimistic CEO using a propensity score matching approach, that is, we match one firm that is managed by an optimistic CEO to a firm that is equally likely to be managed by an optimistic CEO but is indeed managed by a rational CEO. Our results are qualitatively unaffected. The main drawback of this procedure is that we can only match based on observable characteristics. In a second step, we therefore control for unobservable (time-invariant) firm characteristics by testing whether the policy to issue PSD changes after CEO turnover with optimistic successors. We find that optimistic CEOs increase the issuance of PSD after being hired while incoming rational CEOs decrease the fraction of PSD issues. The difference between these two groups is highly significant.

In summary, we show that (i) optimistic managers are more likely to issue PSD than rational managers, (ii) optimistic managers issue PSD with more risk-compensation than rational managers, and (iii) firms with optimistic managers perform worse after issuing PSD than firms with rational managers. These results are robust to controlling for the endogenous choice of employing an optimistic manager.

We make two contributions to the literature. First, we show that managerial traits can have a measurable impact on debt contract design. In particular, we document a positive relationship between managerial optimism and the inclusion of performance-pricing provisions in loan contracts, which have become widespread since the early 1990s. This result extends the existing literature on the impact of managerial traits on corporate financing decisions. For example, Malmendier et al. (2011) and Graham et al. (2012)) show that managerial optimism affects firms' capital structure decisions, while Landier and Thesmar (2009) focus on the effect of debt maturity.[2]

Second, we contribute to the literature on performance-pricing provisions in corporate debt contracts. Asquith et al. (2005) argue that PSD is used to

[2] This list is not intended to be exhaustive. See also Ben-David, Graham, and Harvey (2013), Campbell, Gallmeyer, Johnson, Rutherford, and Stanley (2011), Deshmukh, Goel, and Howe (2010), Ferris, Jayaraman, and Sabherwal (2013), Galasso and Simcoe (2011), Gervais, Heaton, and Odean (2011), Goel and Thakor (2008), Hirhsleifer, Low, and Teoh (2012), Lowe and Ziedonis (2006), Malmendier and Zheng (2012) and Otto (2014). Baker, Ruback, and Wurgler (2004) provide an excellent survey on behavioral corporate finance.

reduce debt renegotiation costs, while Manso et al. (2010) show that PSD can be used as a signaling device for a firm's credit quality. Other studies document a link between PSD and earnings management (Beatty and Weber (2003)), manager equity incentives (Tchistyi, Yermack, and Yun (2011)), and relationship lending (Adam and Streitz (2013)). Our paper is the first to establish a link between the use of PSD and managerial optimism.

The remainder of the paper proceeds as follows. Section 2 presents our hypotheses, while Section 3 describes the sample. Section 4 contains the empirical analysis of the impact of managerial optimism on PSD contract terms. In Section 5 we test the robustness of our results, and Section 6 concludes.

2 Hypothesis Development

In performance-sensitive debt (PSD) the coupon rate is a deterministic function of the issuer's performance. The coupon rises if the borrower's performance deteriorates and/or falls if the borrower's performance improves. Manso et al. (2010) show that PSD can be used as a screening device in a setting with asymmetric information between borrower and lender. In their model, the growth rate of the cash-flow process of a firm is private information and depends on the firm's quality. The lender, who cannot observe the true quality (cash-flow growth rate) of a potential borrower, offers a menu of contracts, which includes fixed-rate debt and risk-compensating PSD. In the resulting separating equilibrium low-growth firms choose to issue fixed-rate debt while high-growth firms choose to issue risk-compensating PSD. The low-growth firm has no incentive to deviate from this equilibrium because despite the initially low coupon rate offered on PSD, PSD subjects the low-growth firm to coupon rate increases in the future when its true type is revealed. Thus, low-growth firms would face higher borrowing costs overall if they were to issue PSD rather than regular debt.

In their model, Manso et al. (2010) assume that the manager of a firm correctly assesses the cash-flow growth rate of his firm and chooses the debt contract according to this expectation. However, the recent literature questions this assumption (e.g., Malmendier and Tate (2005a)). In particular, *optimistic* managers could persistently overestimate the firms' cash-flow growth rate, while *rational* managers correctly assess the firms' cash-flow growth rate on average. As a result, optimistic managers of low-growth firms may now decide to pool with rational managers of high-growth firms.[3] This implies that optimistic managers are more likely to issue PSD than rational managers.

Hypothesis 1: *Optimistic managers are more likely to issue risk-compensating PSD than rational managers.*

Note that for *Hypothesis 1* to hold, we do not require the assumption that the average quality of the firms managed by optimistic managers is less than the quality of firms managed by rational managers. We only require that there are firms for which it is optimal to issue PSD and firms for which it is optimal to issue fixed-rate debt in both groups. Then some low-growth firms that are managed by optimistic managers will issue PSD, as the optimistic manager overestimates the firms' cash-flow growth rate. Firms with a comparable quality that are managed by rational managers will choose fixed-rate debt instead.

Manso et al. (2010) assume for simplicity that there are only two types of firms: low-growth firms and high-growth firms. This assumption can be relaxed without affecting the separating equilibrium. Under the assumption that a continuous distribution of cash-flow growth rates exists, PSD screens different types through different levels of risk-compensation. Fixed-rate debt can simply be considered as a PSD contract with a pricing grid that is flat.

[3] The pooling of optimistic managers with rational managers of high-growth firms preserves the equilibrium as long as the coupon rate increases of PSD adequately compensate the lender for the increase in credit risk due to the presence of some low-growth borrowers.

Consider, for example, a setting with three different types of firms: low-growth, medium-growth, and high-growth. In this situation a separating equilibrium can still be achieved: Low-growth firms choose PSD contracts with no (or low) rate-increase potential, medium growth firms choose PSD contracts with some rate-increase potential, and high-growth firms choose PSD contracts with the highest rate-increase potential. This implies that there must be cross-sectional variation *within* PSD contracts if one allows for a range of different firm types. If optimistic managers generally overestimate the cash-flow growth rate of their firms, this implies that — conditional on choosing PSD — optimistic managers will choose PSD with a higher risk-compensation than rational managers within the same group.

Hypothesis 2: *Optimistic managers choose PSD with more risk-compensation than rational managers.*

Our theory builds on the fact that optimistic managers mimic firms with higher quality by using PSD. If this is the case, then the post-issue firm performance of optimistic managers is expected to be worse than the post-issue firm performance of rational managers using PSD. *Hypothesis 1* stipulates that some low-growth firms with optimistic managers choose PSD contracts and pool with high-growth firms that have a rational manager. Therefore, the set of firms with rational managers that have issued PSD contracts solely consists of high-growth firms, while the set of firms with optimistic managers that have issued PSD contracts consists of both high-growth and low growth firms. This gives rise to our third hypothesis.

Hypothesis 3: *The performance following a PSD issue is worse for firms managed by optimistic managers than for firms managed by rational managers.*

3 Data Description

3.1 Managerial Optimism

We start by classifying CEOs as either rational or optimistic following Malmendier and Tate (2005a), that is, we measure optimism based on executive option holdings. We use ExecuComp to obtain information on executive stock option grants, exercised options, and option holdings. We restrict our sample to the 1992 to 2010 period and exclude financial firms (SIC codes 6000-6999). As ExecuComp contains option exercises only in an aggregated form and not on the grant level, we follow Hall and Liebman (1998) and apply a FIFO-algorithm to construct the option portfolios in a given year.[4] Thereby executives are classified as optimistic if they ever hold an option until maturity, which is at least 40% in-the-money at the year-end prior to maturity.[5] Thus, optimism is considered as an inherent, time-invariant personal characteristic of an executive.

The intuition for relying on the executives' option exercise behavior as a means of classification into rational or optimistic managers is the following: Executives face a trade-off between exercising their options or keeping the options for later exercise. By keeping the options, they maintain the right to purchase company stock at potentially more favorable conditions in the future. The downside of this strategy is that it involves substantial costs for the executive in terms of exposure to idiosyncratic risk. Executive stock options typically have a maturity of ten years and become vested after two to four years. Furthermore, diversifying this exposure is problematic as executives are legally prohibited from short-selling their company's stock. Given the

[4] See Appendix A.3 for further details.

[5] The threshold is derived according to Hall and Murphy (2002) by using a constant risk aversion parameter of 3 and 67% of wealth in company stock. The original Malmendier and Tate (2005b) classification does not require a minimum threshold for in-the-moneyness and solely requires option holding until maturity.

large fraction of personal wealth tied to their company, diversification abilities across alternative investments are also limited. Lastly, besides the financial exposure, also a substantial fraction of the executive's human capital is tied to the company (Malmendier and Tate (2008)). Consequently executives can be considered as under-diversified investors, who have a large exposure to their company's risk. Thus, rational executives should divest as soon as the option is sufficiently in-the-money because the cost of delayed exercise typically exceeds its option value. In contrast, executives who are optimistic and therefore overestimate the firm's future return may fail to exercise their stock options in these situations.

3.2 Loan Sample

We obtain loan contract information from LPC Dealscan for all companies for which the CEO of the borrowing firm can be classified as optimistic or rational.[6] We additionally merge our loan deal panel to COMPUSTAT to obtain financial information on the borrowers.[7] We refer to the Appendix for a detailed description of the control variables used.

Dealscan reports information on performance pricing provisions included in loan contracts. In particular, Dealscan reports the pricing grid, that is, a step function schedule linking the interest payments to a measure of financial performance.[8] We define a dummy variable, PSD, which equals one if a loan contract includes a performance-pricing provision and zero otherwise. We further distinguish between interest-increasing PSD, that is, contracts in

[6] As common in the literature the loan panel is created on the facility (tranche) level (e.g., Berg, Saunders, and Steffen (2013), and Bharath, Dahiyab, Saunders, and Srinivasan (2007)).

[7] We use the link provided by Michael Roberts to merge Dealscan with COMPUSTAT (see Chava and Roberts (2008) for details). We obtain borrower information from the last available fiscal year before the loan issue.

[8] The most common financial measure used in PSD contracts reported in Dealscan is the debt-to-EBITDA ratio ($\sim$ 50% of all PSD loans issued by US borrowers) followed by the senior debt rating ($\sim$ 25%). Other less commonly used measures are the interest coverage ratio, the fixed charge ratio or leverage. A minority of PSD deals uses multiple performance criteria.

which the coupon rate on the loan increases if the borrower's creditworthiness declines, and interest-decreasing PSD, that is, contracts in which the coupon rate on the loan decreases if the borrower's creditworthiness improves. In particular, we define the following ratio:

$$\textit{Rate De-/Increase} = \frac{(S_{Initial} - S_{Min})}{(S_{Max} - S_{Min})}. \tag{1}$$

$S_{Initial}$ is the interest rate paid at contract inception and S_{Max} (S_{Min}) is the highest (lowest) interest rate defined in the pricing grid. *Rate De-/Increase* is zero (one) if the pricing grid allows for interest increases (decreases) only. Contracts with a ratio between zero and one allow for both interest rate increases and interest rate decreases. We define indicator variables for terciles of this ratio to categorize PSD contracts into (mainly) rate-increasing, mixed, and (mainly) rate-decreasing.[9] Disentangling rate-increasing and rate-decreasing PSD is important as our main hypotheses are derived for rate-increasing PSD.[10]

Figure 1 shows the pricing grid of a loan issued by IBM in March 2004 as an example. In this contract, the interest rate changes with IBM's senior debt rating. Since IBM's senior debt rating at the time of the issue was A+, this loan is an example of a mixed PSD contract.

[Figure 1 here]

[9] For robustness we replicated all our specifications defining only contracts as rate-increasing (rate-decreasing) if *Rate De-/Increase* is exactly equal to zero (one). The remaining PSD contracts, that is, contracts with *Rate De-/Increase* between zero an one, are defined as mixed. All our results remain qualitatively unchanged if we use this alternative definition.

[10] The use of rate-decreasing PSD can be motivated by other reasons. For example, Asquith et al. (2005) argue that rate-decreasing PSD is a prepayment option for the borrower, which does not require renegotiation. The interest rate is automatically reduced if there are unanticipated improvements in the borrower's performance, thereby lowering renegotiation costs.

3.3 Descriptive Statistics

We provide descriptive statistics for borrower and loan characteristics in Table 1. We divide the sample into firms managed by optimistic and rational managers. Panel A reports descriptives for borrower characteristics. Unsurprisingly, the companies in our sample are large. By relying on information from the ExecuComp database, which covers all companies listed in the S&P 1,500, we effectively restrict our sample to large public US companies. Borrowers with CEOs that are classified as optimistic are on average smaller compared to borrowers with CEOs that are classified as rational. The mean/median size is $7,452/$2,225 million USD for rational borrowers and $6,502/$2,136 million USD for optimistic borrowers. The other borrower characteristics are similar. Panel B.1 provides descriptive statistics for general loan characteristics. Consistent with *Hypothesis 1*, we find that the fraction of PSD contracts is four % higher in the sample of loans issued by borrowers with optimistic CEOs when compared with loans issued by borrowers with rational CEOs (57% vs. 53%). The median loan amount is $250 for both groups and also the median maturity is similar (about 5 years). Panel B.2 provides descriptive statistics for the subset of performance-sensitive loans. Within PSD contracts firms managed by optimistic managers in particular issue more rate-increasing PSD if compared to firms managed by rational managers.

[Table 1 here]

4 Managerial Optimism and Performance-Sensitive Debt

4.1 Performance-Sensitive vs. Straight Debt

In this section, we analyze the relationship between managerial optimism and the use of PSD. We begin by estimating the following Probit regression specification:

$$PSD_{it} = \alpha + \beta * Optimistic_{it} + \gamma * X'_{it-1} + \delta * Y'_{it} + \epsilon_{it}. \quad (2)$$

The dependent variable, PSD, is a dummy variable, which equals one if the loan contract includes a performance-pricing provision and zero otherwise. *Optimistic* indicates whether the borrowing firm is managed by an optimistic CEO. X is a set of borrower characteristics and Y a set of loan characteristics.[11] We also include industry, time, and rating fixed effects.

[Table 2 here]

The results reported in Table 2 indicate that managerial traits may significantly impact the firms' decision to issue PSD. Loans issued by optimistic CEOs are about six % more likely to contain performance-pricing provisions than loans issued by rational CEOs. Smaller firms are also more likely to issue PSD than larger firms. Furthermore, larger loans and loans that have a longer maturity are more likely to contain performance-pricing provisions. These findings are consistent with the existing literature, which argues that PSD can be used to overcome asymmetric information problems (see Asquith

[11] As noted in the data section, we obtain borrower information from the last available fiscal year *before* the loan issue ($t-1$).

et al. (2005), Manso et al. (2010)), which are more significant in larger loans and loans of longer maturities.

Next, we examine whether the higher likelihood of using PSD by optimistic managers is driven by rate-increasing or rate-decreasing PSD. To do so, we estimate a multinomial logit model, in which the dependent variable can take on four values: 0 for straight debt, 1 for (mainly) rate-increasing PSD, 2 for mixed PSD, and 3 for (mainly) rate-decreasing PSD.

[Table 3 here]

Table 3 shows that the effect reported in Table 2 is solely driven by a preference of optimistic managers for rate-increasing PSD contracts. Optimistic managers are about five % more likely to use rate-increasing PSD, while we find no significant correlation between optimism and mixed or rate-decreasing PSD. Overall, these findings are consistent with *Hypothesis 1*.

4.2 PSD Pricing-Grid Structure

Hypothesis 2 stipulates that optimistic managers choose PSD with more risk-compensation than rational managers. To test this hypothesis we analyze the structure of the PSD pricing grids in more detail. Figure 2, shows the average pricing grid for firms with optimistic and rational CEOs. The graph indicates that the difference between the maximum and the minimum interest rate is on average higher if the CEO of the PSD-issuing firm is optimistic than if the CEO is rational.[12] Of course, the graphical evidence serves as a first indication only, as borrowers with optimistic CEOs and borrowers with rational CEOs are not unconditionally comparable as borrower and loan characteristics may differ.

[12] The median credit rating at the time of the loan issue is BBB+ for both optimistic and rational CEOs, suggesting that the differences in the pricing grids are not driven by differences in the riskiness of the issuing firms.

[Figure 2 here]

To test *Hypothesis 2* in a more refined way, we follow Tchistyi et al. (2011) and calculate slope measures to proxy for the risk of a PSD contract. These slope measures relate interest rate changes that result from a credit rating change (as defined in the pricing grid) to the difference in market interest rates over the same rating notches.[13] A slope of one implies that the pricing grid simply reflects the market interest rate structure at the time of the loan issue. A slope measure greater than one indicates that the borrower "overpays" for downgrades and/or receives a larger interest rate reduction compared to the market for upgrades. To disentangle the up- and downgrade effects we further calculate the slope measure separately over the rate-increasing and the rate-decreasing regions of the pricing grid. Similar to Tchistyi et al. (2011), we also calculate the slope measures "locally" (pricing steps directly adjacent to the initial interest rate) and as averages (average over the entire pricing grid). The local slope measure is formally defined as:

$$LocalSlope = 0.5 * \left(\frac{(S_{i+1} - S_i)}{(Bond_{i+1} - Bond_i)} + \frac{(S_i - S_{i-1})}{(Bond_i - Bond_{i-1})} \right), \quad (3)$$

where S_i is the coupon rate that the borrower pays at the initial rating i. S_{i+1} (S_{i-1}) is the coupon rate, which the borrower has to pay if the company is downgraded (upgraded) and the next pricing step at the rating $i+1$ ($i-1$) is reached.[14] $Bond_i$, $Bond_{i+1}$, and $Bond_{i-1}$ are the levels of the bond market index for the respective rating notches at the time of the loan issue. We use the level of the Bloomberg Bond Market Index for each rating notch at the time of loan issue. As noted above the average slope is calculated similarly by

[13] Note that we can only calculate the slope measures for the subset of PSD contracts that relate interest rate changes to the borrower's credit rating.

[14] Note that we are interested in the risk arising from interest rate changes. For the majority of the PSD contracts the next pricing step is at the next rating notch but this does not have to be the case. Sometimes the same interest rate is defined for more than one rating notch. We only relate actual interest rate changes to changes in the bond market index.

using all interest rate changes defined in the pricing grid. Figure 3 illustrates this procedure.

[Figure 3 here]

The OLS regression results relating the slope of rating-based PSD contracts to managerial optimism are reported in Table 4. We follow Tchistyi et al. (2011) and define the slope of fixed rate debt to be zero.[15] We address skewness in the slope measure by using $ln(Slope)$ in the regressions.

[Table 4 here]

As shown in Table 4, we find — consistent with *Hypothesis 2* — that loans issued by optimistic CEOs have significantly larger local slopes over regions of rating downgrades. This means that optimistic CEOs choose pricing provisions that allow for larger interest rate increases (relative to the market yield) than PSD contracts chosen by rational CEOs. Results for the average slope measures are similar to those for the local slope measures. To summarize, consistent with our hypotheses, optimistic CEOs choose pricing grids with steeper slopes compared with the slopes of the pricing grids chosen by rational CEOs.

4.3 Post-Issue Performance

In this subsection, we test whether firms with optimistic managers perform worse after issuing rate-increasing PSD relative to firms with rational managers (*Hypothesis 3*). In particular, we estimate the following model:

$$\Delta Performance_{it+k} = \alpha + \beta_1 * Optimistic_{it} + \gamma * X'_{it-1} + \delta * Y'_{it} + \epsilon_{it}. \quad (4)$$

[15] We obtain qualitatively the same results if we use a Tobit specification with zero as the lower bound.

$\Delta Performance_{it+k}$ is the change in financial performance of the borrower between the year of the loan issue (t) and k years after the issue ($k = 1, 2$).[16] We use two different measures of firm performance: the debt-to-EBITDA ratio and the firm's credit rating. These two measures are the two most commonly used performance measures in PSD contracts.[17] The regression includes rate-increasing PSD contracts only.[18] We focus on rate-increasing PSD because as shown in Table 3, managerial optimism is related to the use of rate-increasing PSD only. Table 5 presents the regression results.

[Table 5 here]

The results in Columns 1 and 2 show that the debt-to-EBITDA ratio of firms with optimistic CEOs increases in the years following a PSD issue relative to firms with rational CEOs. This effect is economically large. A change of 0.4 (Column 1) represents about one half of the standard deviation of the debt-to-EBITDA ratio. This suggests that the performance (here: leverage) of these firms deteriorates significantly after the loan issue, leading to higher interest payments. In Columns 3 and 4, the dependent variable is a dummy variable, which equals one if the issuer is downgraded following the loan issue and zero otherwise. The results show that the credit rating of firms with optimistic CEOs is about five % more likely to be downgraded following a PSD issue than the credit rating of firms managed by rational CEOs. Again, this result is consistent with the hypothesis that following PSD issues, the performance of firms with optimistic CEOs is worse than the performance of firms with rational CEOs.

[16] Note that, as we are interested in the post-issue performance, we ensure that we measure the firm performance relative to the first financial statement *after* the loan issue to ensure that we do not simply capture the effect of the loan issue itself. $t+1$ ($t+2$) therefore refers to the 2nd (3rd) financial statement after the loan issue, that is, to a point in time that is on average more than one (two) calendar year(s) after the loan issue.

[17] More than 75% of all PSD contracts are written on either the issuer's credit rating or the issuer's debt-to-EBITDA ratio.

[18] Using both PSD and straight debt contracts and interacting *Optimistic* with a PSD indicator variable yields qualitatively similar results.

Note that the results in Table 5 also rule out a possible alternative explanation of our results. Delaying the exercise of an in-the-money option can be a rational strategy if the manager possesses positive inside information. Therefore, being *optimistic* may capture positive inside information of a manager and not only irrational over-optimism. In this case, "optimistic" managers may issue PSD simply because they possess positive inside information about the firm's future performance. However, if this were the case, we would expect firm performance to be better than that of rational managers following a PSD issue. Our findings show that the opposite is the case.

4.4 Endogeneity

A potential concern with our analysis is that managerial optimism may be an endogenous choice by the firm's owners when selecting a CEO. The same factors that drive the choice of the CEO could in principle also determine the use of PSD. In order to address this problem we use a propensity score matching approach and estimate the probability that a firm is managed by an optimistic CEO. For example, Hirhsleifer et al. (2012) argue that a reason for hiring optimistic CEOs might be that optimistic managers are more likely to invest in more innovative and riskier projects and can thereby benefit shareholders. We explicitly control for firm age in the first stage regression because innovations are more important in younger firms.[19] Furthermore, we use several firm characteristics, such as total assets, leverage, market-to-book, asset tangibility, interest coverage, profitability, current ratio, and industry-, year- and credit rating (notch level) fixed effects as additional explanatory variables. In untabulated results we find that firms with lower leverage ratios, higher market-to-book ratios, lower interest coverage ratios, and younger firms are more likely to be managed by optimistic CEOs. In the next step we match

[19] We compute firm age based on the data provided by Laura Field and Jay Ritter available on http://bear.warrington.ufl.edu/ritter/foundingdates.htm. The data is described in detail in Loughran and Ritter (2004). Firm founding dates are only available for roughly 50% of our sample, which leads to a sample reduction in Table 6.

firms based on the probability to be managed by an optimistic CEO, that is, we match one firm that is managed by an optimistic CEO to a firm that is predicted to be managed by an optimistic CEO but is indeed managed by a rational CEO.

[Table 6 here]

In Table 6 we report results of a probit regression specification as in Table 2 for the matched sample. We find that optimistic CEOs are eight to nine % more likely to issue performance-sensitive debt contracts (compared to rational CEOs). Thus, our results are even stronger after accounting for a possibly endogenous selection of optimistic CEOs.

A drawback of the propensity score matching technique is that the choice to hire an optimistic CEO can only be modeled based on observable firm characteristics. To control for unobservable time-invariant firm characteristics that might be correlated with the use of PSD and managerial optimism, we examine PSD issuance after CEO turnover.

In particular, we compare the use of PSD of incoming optimistic CEOs with the use of PSD of incoming rational CEOs three years before and three years after the turnover event.[20] We are forced to disregard the type of the outgoing CEOs due to sample size restrictions. Since we can only classify a fraction of all CEOs as either optimistic or rational,[21] further conditioning our analysis on the type of outgoing CEO would render the sample size to be too small for statistical inference. Not conditioning on the type of the outgoing CEO, however, is conservative as it biases our tests against finding a statistically significant relationship.

[20] The results are qualitatively similar if we vary the event window and use, for example, five years before and after the turnover.
[21] Cf. section 3.1.

We estimate two separate linear probability models with a dummy variable equal to one if the company issues a loan with a performance-pricing provision and zero otherwise as dependent variable. The first column includes only observations where the incoming CEO is optimistic, the second column only observations where the incoming CEO is rational. Both regressions include the same control variables as in Table 2. To see whether optimistic CEOs pursue a different policy with respect to the use of PSD we estimate a difference-in-differences model. The first difference is calculated as the difference between the fraction of loans with a performance-pricing feature before and after the CEO turnover, represented by the coefficient *Post Turnover*. The second difference is the difference in the coefficient *Post Turnover* between optimistic and rational CEOs.

[Table 7 here]

Our results are presented in Table 7. We find that optimistic CEOs significantly increase the fraction of loans with a performance-pricing provision while rational CEOs seem to decrease the fraction of PSD (although not significantly). The difference between both coefficients is significantly different from zero suggesting that optimistic CEOs are more likely to issue PSD relative to rational CEOs even after controlling for unobservable, time-invariant firm effects.

5 Robustness

5.1 Other Optimism Measures

In this section, we analyze whether our results are robust to alternative methods to identify optimistic managers. In particular, we consider different moneyness thresholds for the original optimism classification, distinguish between Pre- and Post-Optimistic, and consider alternative methods to identify optimism.

[Table 8 here]

Table 8 replicates Table 2 but uses alternative optimism measures. In Columns 1 and 2 we use more conservative moneyness thresholds than in our original optimism classification. In particular, we identify executives as optimistic if they ever hold an option until one year prior to expiration, which is at least 70% in-the-money (Column 1) or at least 100% in-the-money (Column 2). The original classification uses a moneyness threshold of 40%. The results in Table 8 confirm our previous findings. Firms managed by optimistic CEOs are significantly more likely to include a performance-pricing provision in their loan contracts than firms managed by rational CEOs. Thus, our results are not sensitive to the choice of the moneyness parameter, which is also consistent with the robustness checks in Malmendier and Tate (2008).

Next, we follow Malmendier and Tate (2008) and distinguish between the time before and after an optimistic manager has ever shown evidence of being optimistic. The motivation for this separation is to justify the treatment of optimism as a time-invariant, personal characteristic. *Pre-Optimistic* refers to the time period before the respective executive first holds an option that is at least 40% in-the-money until the final maturity year, and *Post-Optimistic* refers to the time period thereafter. Table 8 shows that optimistic CEOs are significantly more likely to use PSD than rational CEOs, both before and after they are classified by our algorithm. This finding supports the notion that optimism is a time-invariant, personal characteristic.

In Column 4 we employ a different identification method of optimism, suggested by Malmendier and Tate (2005b). According to this method, CEOs are classified as optimistic if they hold stock options that are at least 67% in the money five years after the respective option grants. A CEO needs to show this behavior at least twice during his tenure to be classified as optimistic. Malmendier and Tate (2005b) refer to this measure as *Holder 67*.[22] Using the *Holder 67* measure instead of the original optimism variable, our results are even stronger than before.

In Column 5, we use a new identification method of optimism first proposed by Sen and Tumarkin (2009). Instead of analyzing executives' option exercise behavior, this method examines the executives' stock holdings. An executive is classified as optimistic if his total stock holdings relative to his salary exceed the median stock holdings to salary ratio. The intuition for this classification is similar to the *Optimistic* classification. Executives are generally poorly diversified and have a large idiosyncratic risk exposure to their firms. Consequently, they should hold as little of their companies' stock as possible. If executives voluntarily hold more stock, they are likely to be overly optimistic with respect to the future performance of their firms. According to Core and Larcker (2002), many firms have a minimum stock holding requirement for their top executives in place, which often is stated in terms of multiples of the executives' salary. Like Sen and Tumarkin (2009) we use the median of this stock holdings-to-salary multiple as our threshold to distinguish between rational and optimistic executives. Again, the results in Table 8 confirm our previous findings that firms with optimistic CEOs are more likely to use performance-pricing provisions than firms managed by rational CEOs. In summary, our findings are robust to several alternative optimism specifications.

5.2 CEO Characteristics

Bertrand and Schoar (2003) show that managerial style, which is likely to be affected by manager characteristics such as age, gender or educational background, significantly affects corporate financial policy. For example, Be-

[22] We are grateful to Rik Sen for providing us with this measure.

ber and Fabbri (2010) find that CEO age and education is correlated with speculation in the FX market. Huang and Kisgen (2013) find that male executives make riskier financial and investment decisions than female executives. Kaplan, Klebanov, and Sorensen (2012) find that general CEO ability and execution skills matter in buyout and venture capital transactions. To address the concern that our optimism measure may be correlated with CEO characteristics that also affect risk-taking and therefore the decision to issue PSD, we explicitly control for CEO age, tenure, gender, and education in this section.

In addition to personal managerial characteristics, executive compensation plans are likely to also affect risk-taking behavior. In the context of PSD, Tchistyi et al. (2011) document that managers whose compensation is more sensitive to stock return volatility choose riskier pricing grids. To rule out the possibility that our results are driven by a correlation between the optimism measures and the delta/vega of the CEOs stock option portfolio, we explicitly control our analysis for these sensitivities. We follow Core and Guay (2002) in calculating delta and vega. The results are reported in Table 9.

[Table 9 here]

Besides optimism, the only variable that is significantly correlated with the decision to issue PSD is age, that is, the age of the CEO at the time of the debt issue (in years). Older CEOs are less likely to issue loans that contain performance-pricing provisions than younger CEOs. The other personal characteristics, as well as the delta and the vega of the CEO's stock and option portfolio are not significantly related to the decision to issue PSD. As noted above, controlling for delta and vega mitigates concerns that our optimism measure is positively correlated with a larger general risk preference by those executives.

6 Conclusion

This paper explores the impact of managerial optimism on debt contract design. In particular, we investigate whether optimistic CEOs, that is, managers who persistently overestimate their firms' future expected cash flow, are more likely to issue performance-sensitive debt (PSD) than rational managers. This possibility arises when optimistic managers decide to pool with rational managers who signal their credit worthiness using PSD.

We find that optimistic managers are indeed more likely to issue PSD than rational managers. We further find that within the subset of PSD issuing firms, optimistic managers choose contracts with larger risk-compensation to lenders, that is, pricing grids with more coupon rate increase potential in response to performance deterioration. Finally, we find that firms managed by optimistic managers perform worse after a PSD issue compared to firms managed by rational managers. This result confirms that our results are not simply driven by optimistic managers possessing some information advantage relative to rational managers. Our results are robust to the endogenous choice of the CEO as well as several robustness checks. Overall, our results suggest that managerial optimism can have a significant impact on a firm's debt contract design.

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Appendix

A.1 Figures

Figure 1: PSD Pricing Grid Example

This figure exemplary shows the pricing grid embedded in the loan contract negotiated by International Business Machines Corporation (IBM) in March 2004. Information are taken from the Dealscan database. The black line shows the interest rate contingent upon the issuers credit rating. IBM's credit rating at the time of the loan issues was A+, the initial interest rate LIBOR + 12bp.

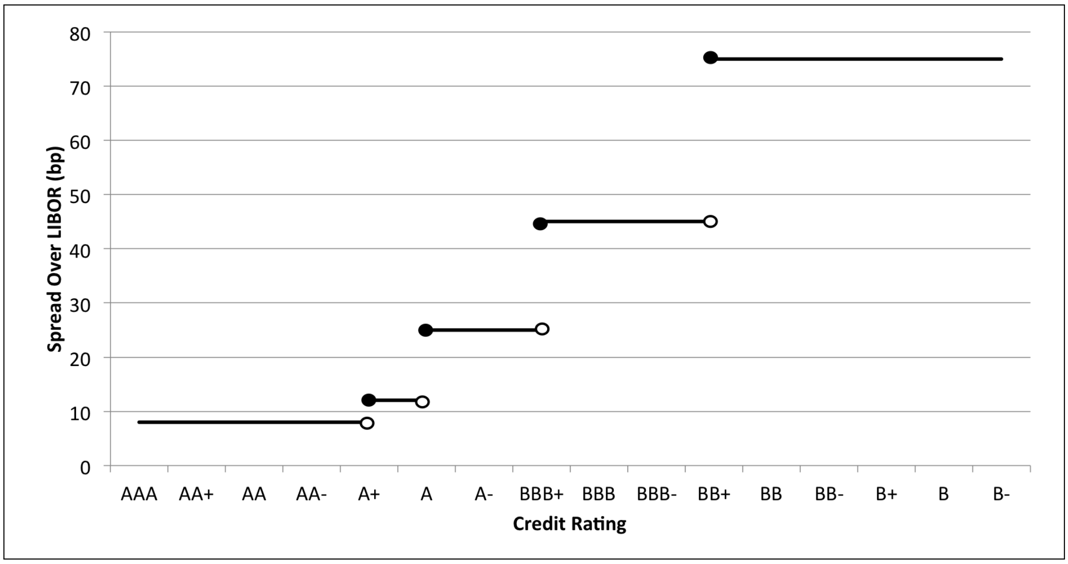


Figure 2: PSD Pricing Grids - Optimistic vs. Rational CEOs

This figure shows pricing grids for firms with optimistic CEOs (straight line) and rational CEOs (dashed line). The pricing grid is calculated by taking the average spread over LIBOR for each rating notch relative to the spread paid when the rating is AAA. These calculations are performed for both groups individually.

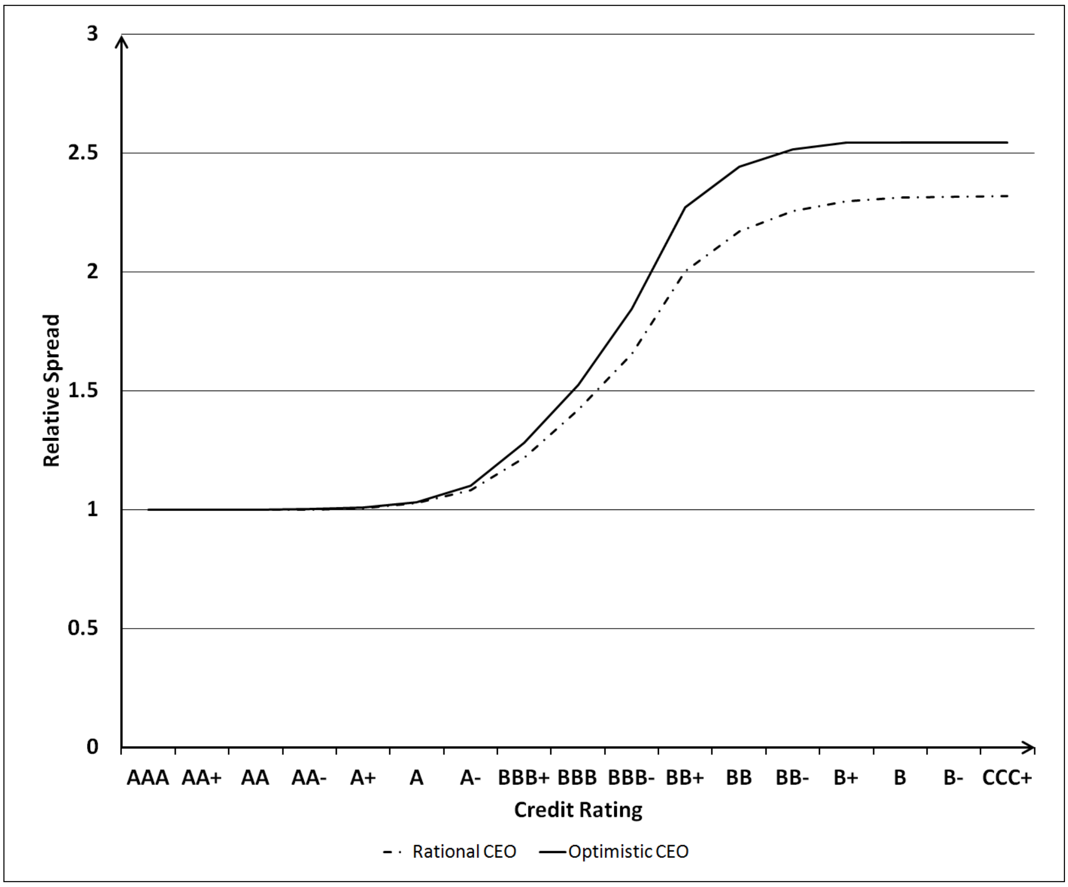


Figure 3: Slope of the PSD Pricing Grid

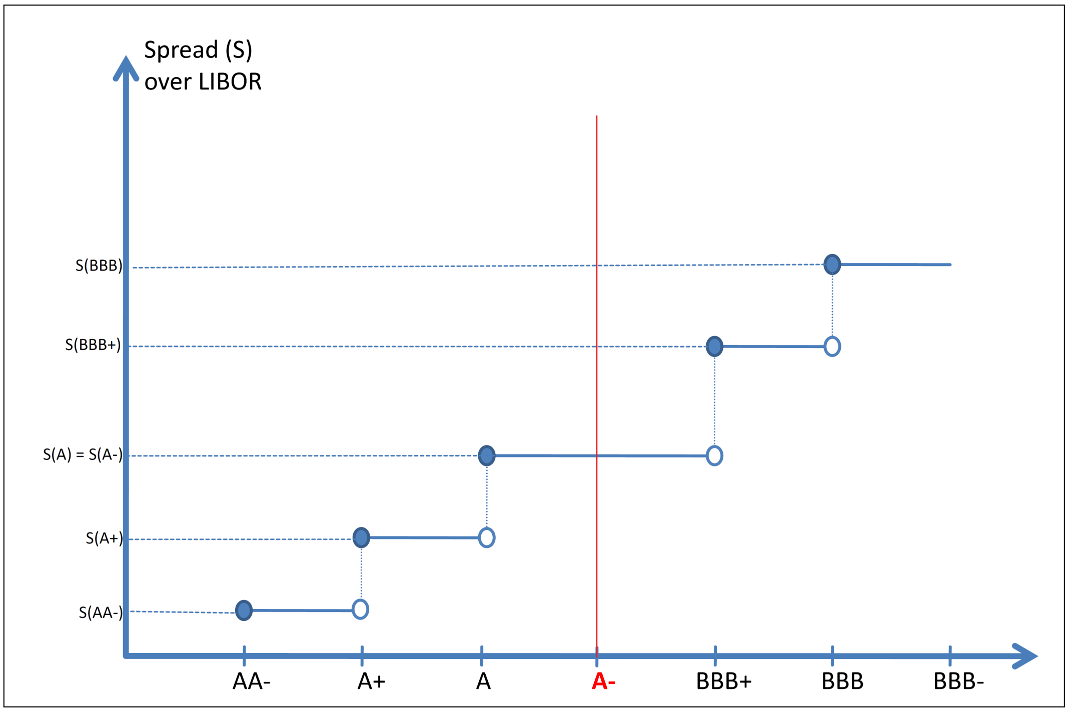
This figure shows a hypothetical rating-based performance pricing grid that links the borrower's credit rating to the interest rate S over a benchmark (e.g. LIBOR). Interest payments increase if the rating deteriorates and decline if the rating improves. This hypothetical pricing grid is defined over the ratings AA- to BBB. The rating as of loan issue is A-. The local measures are calculated over the pricing steps adjacent to the initial rating while the average measures are calculated over the entire pricing grid. The definitions of the local slope measures for this hypothetical performance pricing grid are:

$$\text{Local Slope} = 0.5 * \left(\frac{(S_{BBB+} - S_{A-})}{(Bond_{BBB+} - Bond_{A-})} + \frac{(S_{A-} - S_{A+})}{(Bond_{A-} - Bond_{A+})} \right)$$

$$\text{Local Slope} \uparrow = \frac{(S_{A-} - S_{A+})}{(Bond_{A-} - Bond_{A+})}$$

$$\text{Local Slope} \downarrow = \frac{(S_{BBB+} - S_{A-})}{(Bond_{BBB+} - Bond_{A-})}$$

The average slopes are calculated similar to the local slope measure but using all pricing steps that are defined in the grid.



A.2 Tables

Table 1: Descriptive Statistics: Rational vs. Optimistic CEOs

This table reports descriptive statistics for loan and borrower characteristics. The sample is divided into firms with rational and optimistic CEOs. All variables are defined in Appendix A.4.

	Rational CEOs				Optimistic CEOs			
	Mean	Median	Std. Dev	#	Mean	Median	Std. Dev	#
Panel A: Borrower Characteristics								
Total Assets (million USD)	7,452.15	2,224.88	14,060.66	4,500	6,501.62	2,135.63	13,205.37	2,434
Leverage	0.27	0.26	0.19	4,500	0.25	0.24	0.16	2,434
Market-To-Book	1.78	1.48	0.95	4,500	1.87	1.60	0.95	2,434
Tangibility	0.35	0.29	0.23	4,500	0.33	0.26	0.24	2,434
Coverage	22.11	7.10	52.11	4,500	22.42	9.19	49.37	2,434
Profitability	0.18	0.15	0.15	4,500	0.17	0.14	0.13	2,434
Current Ratio	1.75	1.50	1.05	4,500	1.77	1.57	0.99	2,434
Not Rated (0/1)	0.31	0.00	0.46	4,500	0.31	0.00	0.46	2,434
Investment Grade (0/1)	0.43	0.00	0.50	4,500	0.46	0.00	0.50	2,434
Panel B.1: General Loan Characteristics								
Facility Amount (million USD)	537.39	250.00	987.89	4,500	539.44	250.00	1,021.55	2,434
Maturity (months)	44.16	50.00	23.08	4,500	43.99	55.00	22.58	2,434
Multiple Tranches (0/1)	0.42	0.00	0.49	4,500	0.44	0.00	0.50	2,434
Term Loan (0/1)	0.20	0.00	0.40	4,500	0.18	0.00	0.38	2,434
Secured	0.37	0.00	0.48	4,500	0.33	0.00	0.47	2,434
PSD (0/1)	0.53	1.00	0.50	4,500	0.57	1.00	0.49	2,434
Panel B.2: PSD Characteristics								
PSD(Rating) (0/1)	0.43	0.00	0.50	2,367	0.44	0.00	0.51	1,397
PSD(Accounting) (0/1)	0.58	1.00	0.49	2,367	0.57	1.00	0.50	1,397
PSD(Increasing) (0/1)	0.12	0.00	0.33	2,367	0.14	0.00	0.35	1,397
PSD(Mixed) (0/1)	0.67	1.00	0.47	2,367	0.65	1.00	0.48	1,397
PSD(Decreasing) (0/1)	0.19	0.00	0.39	2,367	0.18	0.00	0.39	1,397
# Pricing Steps	4.73	5.00	1.30	2,367	4.71	5.00	1.31	1,397

Table 2: Performance-Sensitive vs. Straight Debt

This table reports the marginal effects for a probit regression using a dummy as the dependent variable that equals one whenever a loan includes a performance pricing provision and zero otherwise. The main variable of interest is *Optimistic*, which is an indicator variable that equals one if the CEO of the borrower is classified as optimistic and zero otherwise. All variables are defined in Appendix A.4. Marginal effects for each covariate are constructed as the difference in predicted probabilities for a particular outcome computed at their mean values holding all other covariates constant. For factor levels it is computed as a discrete change from the base level. The regressions include time, industry, and rating (notch level) dummies when indicated. Standard errors are heteroskedasticity robust and clustered at the firm level to account for non-independent observations within firms. *, **, *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	(1)	**(2)**	**(3)**	**(4)**
Panel A: Optimism Classification				
Optimistic	0.063***	0.061***	0.058***	0.057***
	(0.022)	(0.022)	(0.022)	(0.022)
Panel B: Borrower Characteristics				
ln(Total Assets)			−0.032***	−0.097***
			(0.011)	(0.013)
Leverage			−0.088	−0.096
			(0.069)	(0.069)
Market-to-Book			−0.003	−0.004
			(0.012)	(0.012)
Tangibility			−0.092	−0.043
			(0.072)	(0.075)
Coverage			0.000	0.000
			(0.000)	(0.000)
Profitability			0.124	−0.002
			(0.090)	(0.089)
Current Ratio			−0.017	−0.011
			(0.012)	(0.012)
Panel C: Loan Characteristics				
ln(Facility Amount)				0.136***
				(0.010)
ln(Maturity)				0.119***
				(0.012)
Multiple Tranches				0.073***
				(0.017)
Term Loan				−0.233***
				(0.020)
Secured				0.154***
				(0.022)
Observations	6,749	6,703	6,703	6,703
Pseudo R^2	0.060	0.074	0.078	0.154
Year Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	No	Yes	Yes	Yes
Credit Rating Fixed Effects	Yes	Yes	Yes	Yes

Table 3: Interest Increasing vs. Interest Decreasing PSD

This table reports the marginal effects for a multinominal logit regression using a dummy as the dependent variable, which equals one for PSD contracts that contain mainly spread increase features (Column 1), two for PSD contracts that contain both spread increase and spread decrease features (Column 2), three for PSD contracts that contain mainly spread decrease features (Column 3) and zero for non-PSD contracts (base group). The main variable of interest is *Optimistic*, which indicates the probability of optimistic CEO to choose a loan contract with the respective spread change feature. The regressions furthermore include all control variables used in Table 2. All variables are defined in Appendix A.4. Marginal effects for each covariate are constructed as the difference in predicted probabilities for a particular outcome computed at their mean values holding all other covariates constant. For factor levels it is computed as a discrete change from the base level. The regressions include time, industry, and rating (notch level) dummies. Standard errors are heteroskedasticity robust and clustered at the firm level to account for non-independent observations within firms. *, **, *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	(1)	**(2)**	**(3)**
Optimistic	0.044***	0.007	0.007
	(0.017)	(0.012)	(0.005)
Observations	6,718		
Pseudo R^2	0.182		
Firm Characteristics	Yes		
Loan Characteristics	Yes		
Year Fixed Effects	Yes		
Industry Fixed Effects	Yes		
Credit Rating Fixed Effects	Yes		

Table 4: Managerial Optimism and the Slope of PSD Contracts

This table reports OLS regressions, relating the slope of the performance pricing grids to CEO, borrower and loan characteristics. The sample includes straight debt contracts and rating-based PSD contracts. The dependent variables are slope measures for the PSD pricing grids. The local slope is defined as follows.

$$\mathit{Local\ Slope} = 0.5 * \left(\frac{(S_{i+1} - S_i)}{(Bond_{i+1} - Bond_i)} + \frac{(S_i - S_{i-1})}{(Bond_i - Bond_{i-1})} \right)$$

S_i is the spread that the borrower pays at the initial rating i. S_{i+1} (S_{i-1}) is the spread hat the borrower has to pay when the company is downgraded (upgraded) and the next pricing step at the rating $i+1$ ($i-1$) is reached. $Bond_i$, $Bond_{i+1}$, and $Bond_{i-1}$ are the levels of the bond market index for the respective rating notches at the time of the loan issue. The slope of straight debt is 0. While the *Local Slope* is defined over the pricing steps directly adjacent to the initial pricing step only, the *Average Slope* is calculated as a mean over all pricing steps defined in the grid. *Local Slope* ↑ and *Average Slope* ↑ are defined over all credit ratings above the firm's rating at the time of contract inception, i.e. for rating upgrades. *Local Slope* ↓ and *Average Slope* ↓ are defined over all credit ratings below the firm's rating at the time of contract inception, i.e. for rating downgrades. The main independent variable of interest is *Optimistic*, which is an indicator variable, which equals one if the CEO of the borrower is classified as optimistic and zero otherwise. The regressions furthermore include all control variables used in Table 2. All variables are defined in Appendix A.4. The regressions include time, industry, and rating (notch level) dummies. Standard errors are heteroskedasticity robust and clustered at the firm level to account for non-independent observations within firms. *, **, *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	(1) Local Slope	(2) Local Slope ↑	(3) Local Slope ↓	(4) Average Slope	(5) Average Slope ↑	(6) Average Slope ↓
Optimistic	0.014**	0.006	0.018***	0.012*	0.009	0.014**
	(0.007)	(0.006)	(0.007)	(0.007)	(0.006)	(0.007)
Observations	4,502	4,365	4,428	4,502	4,366	4,430
Adj. R^2	0.228	0.206	0.210	0.229	0.230	0.208
Firm Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Loan Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Credit Rating Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Continued on next page

Table 4 – continued from previous page

	(1) Local Slope	(2) Local Slope ↑	(3) Local Slope ↓	(4) Average Slope	(5) Average Slope ↑	(6) Average Slope ↓

Table 5: Post-PSD-Issue Performance

This table reports OLS regressions showing the change in Debt-to-EBITDA between the year of the loan issue *(t)* and k years after the issue *(k = 1,2)*. The sample is restricted to PSD contracts with a spread-increase potential. This table further reports marginal effects of probit regressions using a dummy as the dependent variable, which equals one if the borrowing firm was downgraded k years after the issue of PSD. Again, the sample is restricted to PSD contracts with a spread-increase potential. Marginal effects for each covariate are constructed as the difference in predicted probabilities for a particular outcome computed at their mean values holding all other covariates constant. For factor levels it is computed as a discrete change from the base level. Standard errors are heteroskedasticity robust and clustered at the firm level to account for non-independent observations within firms. *, **, *** indicate statistical significance at the 10%, 5% and 1% level, respectively. The regressions include time, rating, and insdustry fixed effects, as well as loan, and borrower characteristics. All variables are defined in Appendix A.4.

	(1)	**(2)**	**(3)**	**(4)**
	Δ Debt-to-EBITDA		Rating Downgrade	
	$k = 1$	$k = 2$	$k = 1$	$k = 2$
Optimistic	0.401**	0.350*	0.052*	0.021
	(0.155)	(0.185)	(0.028)	(0.042)
Observations	2,341	2,193	941	913
Adjusted R^2	0.032	0.042		
Pseudo R^2			0.105	0.057
Control Variables	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Credit Rating Fixed Effects	Yes	Yes	Yes	Yes

Table 6: Propensity Score Matching - PSD vs. Straight Debt

This table reports the marginal effects for the second stage of a propensity score matching model using a dummy as the dependent variable that equals one whenever a loan includes a performance-pricing provision and zero otherwise. The propensity scores are estimated in the first stage by a probit regression using a dummy as the dependent variable that equals one if the firm is managed by an optimistic CEO and zero otherwise. *Optimistic* is an indicator variable that equals one if the CEO of the borrower is classified as optimistic, i.e., if the CEO ever held an option until the final maturity year, which is at least 40% in the money and zero otherwise. The regressions furthermore include all control variables used in Table 2. All variables are defined in Appendix A.4. Marginal effects for each covariate are constructed as the difference in predicted probabilities for a particular outcome computed at their mean values holding all other covariates constant. For factor levels it is computed as a discrete change from the base level. The regressions include time, industry, and rating (notch level) dummies. Standard errors are heteroskedasticity robust and clustered at the firm level to account for non-independent observations within firms. *, **, *** indicate statistical significance at the 10%, 5% and 1% level respectively.

	(1)	**(2)**
Optimistic	0.090***	0.082**
	(0.033)	(0.033)
Observations	1,716	1,716
Pseudo R^2	0.127	0.219
Firm Characteristics	Yes	Yes
Loan Characteristics	No	Yes
Year Fixed Effects	Yes	Yes
Industry Fixed Effects	Yes	Yes
Credit Rating Fixed Effects	Yes	Yes

Table 7: CEO Turnover - PSD vs. Straight Debt

This table reports results for fixed effects linear probability models using a dummy as the dependent variable which is equal to one whenever a loan includes a performance pricing provision and zero otherwise. The sample solely includes loans issued during the three years before and after CEO turnover. Further, it includes only observations where the new CEO can be classified as optimistic or rational. In total, the sample comprises 161 CEO changes. *Post Turnover* is an indicator variable which equals one if the loan was issued in the three years following CEO turnover. In model (1), loan issues are included where the incoming CEO was classified as optimistic. In model (2), we include loan issues where the incoming CEO was classified as rational. The regressions furthermore include all control variables used in Table 2. All variables are defined in Appendix A.4. The regressions include time, rating (notch level), and firm fixed effects. *, **, *** indicate statistical significance at the 10%, 5% and 1% level respectively.

	(1)	**(2)**
Post Turnover	0.295**	−0.058
	(0.148)	(0.082)
Observations	236	620
Adj. R^2	0.530	0.449
Firm Characteristics	Yes	Yes
Loan Characteristics	Yes	Yes
Year Fixed Effects	Yes	Yes
Credit Rating Fixed Effects	Yes	Yes
Firm Fixed Effects	Yes	Yes

Test if coefficients are equal in both models:

Post Turnover (Optimistic) = Post Turnover (Rational)

$\chi^2(1) = 5.15$

Prob $> \chi^2 = 0.0233$**

Table 8: Alternative Optimism Classifications

This table reports the marginal effects for probit regressions using a dummy as the dependent variable that equals one whenever a loan includes a performance pricing provision and zero otherwise. *Optimism 70* and *Optimism 100* are indicator variables that equal one if the CEO of the borrower is classified as optimistic, i.e. if the CEO ever held an option until the final maturity year, which is at least 70 or 100% in the money and zero otherwise. *Holder67* is an indicator variable that is equal to one if CEOs did not exercise options that were at least 67% in the money in their fifth year at least twice during their tenure. *Pre-Optimistic* and *Post-Optimistic* indicate the time period before an executive ever held an option until the final maturity year, which is at least 40% in the money and the the time period after this activity, respectively. Voluntary Holder is an indicator variable that equals one if CEOs voluntarily holds more stocks of their company than required by company constitutions. The regressions furthermore include all control variables used in Table 2. All other variables are defined in Appendix A.4. Marginal effects for each covariate are constructed as the difference in predicted probabilities for a particular outcome computed at their mean values holding all other covariates constant. For factor levels it is computed as a discrete change from the base level. The regressions include time, industry, and rating (notch level) dummies. Standard errors are heteroskedasticity robust and clustered at the firm level to account for non-independent observations within firms. *, **, *** indicate statistical significance at the 10%, 5% and 1% level respectively.

	(1)	(2)	(3)	(4)	(5)
Optimistic (70)	0.050**				
	(0.024)				
Optimistic (100)		0.055**			
		(0.025)			
Pre-Optimistic			0.062**		
			(0.028)		
Post-Optimistic			0.050*		
			(0.027)		
Holder 67				0.077***	
				(0.027)	
Voluntary Holder					0.062***
					(0.023)
Observations	6,703	6,703	6,703	3,379	6,417
Pseudo R^2	0.153	0.153	0.154	0.167	0.147
Firm Characteristics	Yes	Yes	Yes	Yes	Yes
Loan Characteristics	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
Credit Rating Fixed Effects	Yes	Yes	Yes	Yes	Yes

Table 9: CEO Characteristics

This table reports the marginal effects for probit regressions using a dummy as the dependent variable that equals one whenever a loan includes a performance pricing provision and zero otherwise. *Optimistic*is and indicator variables that equal one if the CEO of the borrower is classified as optimistic, i.e. if the CEO ever held an option until the final maturity year, which is at least 40% in the money and zero otherwise. *Female* is a dummy variable that is equal to one if the CEO is female. *Ph.D.* is a dummy variable if the CEO holds a Ph.D. degree. *Tenure* is the time in days since the executive became CEO. *Delta* measures the sensitivity of the CEO's overall option and stock portfolio to price movements of the company's stock. *Vega* measures the sensitivity of the CEO's overall option and stock portfolio to volatility changes of the company's stock. The regressions furthermore include all control variables used in Table 2. All variables are defined in Appendix A.4. Marginal effects for each covariate are constructed as the difference in predicted probabilities for a particular outcome computed at their mean values holding all other covariates constant. For factor levels it is computed as a discrete change from the base level. The regressions include time, industry, and rating (notch level) dummies. Standard errors are heteroskedasticity robust and clustered at the firm level to account for non-independent observations within firms. *, **, *** indicate statistical significance at the 10%, 5% and 1% level respectively.

	(1)	**(2)**	**(3)**
Optimistic	0.057**	0.053**	0.050**
	(0.023)	(0.023)	(0.023)
Female	−0.023		−0.041
	(0.080)		(0.084)
Ph.D.	0.016		−0.001
	(0.057)		(0.059)
Age	−0.003**		−0.003*
	(0.001)		(0.002)
Tenure	0.001		0.002
	(0.002)		(0.002)
Delta		−0.150	−0.133
		(0.271)	(0.275)
Vega		−0.002	−0.001
		(0.005)	(0.005)
Observations	6,567	6,139	6,008
Pseudo R^2	0.154	0.149	0.150
Firm Characteristics	Yes	Yes	Yes
Loan Characteristics	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes
Credit Rating Fixed Effects	Yes	Yes	Yes

A.3 Optimism Classification

We follow Malmendier and Tate (2005a) and classify executives as optimistic if they ever hold an option until one year before expiration even though the option is at least 40% in the money. Therefore, to identify executives as optimistic we need detailed information about the portfolio of executive stock option holdings for each executive at different points in time. Before 2006, ExecuComp contains information on option holdings only in an aggregated form and not detailed for each position of the option portfolio. Therefore, we use information on option grants and option exercises in order to infer detailed information on option portfolios including time to maturity and strike price. Option grants are provided in a detailed manner in the ExecuComp tables STGRTTAB and PLANBASEDAWARDS. Option exercises are given in an aggregated form in the table ANNCOMP. Thus, ExecuComp does only state how many options were exercised but not from which option grant. Therefore, we follow Hall and Liebman (1998) and assume a first-in first-out (fifo) allocation rule in order to infer the option holdings per year.

In doing so, we follow Hall and Liebman (1998) and make the following assumptions:

1. Missing information on option grants.

For each option grant we require the number of options granted, the expiration date and the exercise price. Information on option grants is given in the ExecuComp tables STGRTTAB (until 2006) and PLANBASEDAWARDS (from 2006 onwards). Information on the expiration date of the grant is contained in the table OUTSTANDINGAWARDS. When exercise dates are missing, we assume that the option expires ten years after the grant date as the median maturity for all option grants is ten years. When the grant date is missing, we assume that the options are granted at fiscal year end. When the exercise price is missing, we assume that the options are granted at the money and thus replace missing exercise prices with the stock price of the company at the grant date.[23]

2. Inconsistencies in granted options between PLANBASEDAWARDS & STGRTTAB and ANNCOMP

We compare whether the number of options granted reported in the tables STGRTTAB and PLANBASEDAWARDS matches with the information given in the annual compensation table ANNCOMP. In approximately 95% of observations this is the case. For the remaining observations only general information on granted options is given in ANNCOMP but no detailed information is available in STGRTTAB or PLANBASEDAWARDS. In these cases, we assume that the options are granted in a single grant at the money at fiscal year end.

3. Missing years in compensation reporting

We check whether there are missing years in the compensation reporting for managers in ExecuComp (for example if compensation is reported for a manager in 1994 and 1996 but not in 1995). If this is the case, we do not know how many options were granted or exercised in the missing years and we only observe the total number of options held in the year following the missing years. When there is only a gap of one year, the missing information can be obtained by comparing the option holdings of the year before the gap and the year following the gap. When the number of options held is larger in the year following the gap we assume that the additional options are granted in a single grant at the money at fiscal year end of the missing year. When the number of options in the following year is smaller than in the year before the gap, we

[23] The stock price at the grant date is included in the ExecuComp database as the variable "mktpric". If this variable is not available we use instead the CRSP stock price of the company at the grant date.

assume that the difference is exercised in the missing year. Thereby we apply the first-in first-out principle and assume that the oldest options are exercised first.

4. Initial option holdings

ExecuComp contains data on executive compensation starting in 1992. We follow Hall and Murphy (2002) and restrict our sample to managers that are included in ExecuComp ten years after ExecuComp's initial year, that is, 2002, and the years thereafter. This ensures that we can backtrack option grants and exercises for managers for a sufficient period of time. The reasoning behind this is that executive stock options typically have a maturity of ten years and including only executives in 2002 or thereafter makes sure that the option portfolios that we compute using the fifo technique are not biased by imposing too many assumptions on initial option holdings. Hereby, we ensure that the option portfolios we analyze include reliable information on maturity and strike price.

However, also managers that appear in ExecuComp for the first time after 2002 sometimes already have initial stock option holdings for which we do not have information on the strike price and the maturity. We follow Hall and Liebman (1998) and assume that these options are granted three years earlier and have seven years left until expiration (i.e., they are granted with a ten year maturity). We further assume that the options are granted at the money at fiscal year end.

5. Inconsistencies in option holdings between fifo-algorithm & ANNCOMP

Sometimes the fifo-algorithm results in a different number of options held by the executive than the number reported in the annual compensation table ANNCOMP. If this is the case, we follow Hall and Liebman (1998) and impose the following assumptions to the option holdings. (i) When the number of options held by the executive given in ANNCOMP is smaller than the number computed by the fifo-algorithm, we assume that either some exercises are missing in ExecuComp or that some options expired. Therefore, we subtract the difference from the oldest option grants. (ii) When the number of options held given in ANNCOMP is larger than the number computed by the fifo-algorithm, we assume that too many options were exercised and add back the exercised options until both numbers match. If it is insufficient to add back the exercised options to reach the number reported in ANNCOMP, the option holdings are rescaled proportionally such that they match with the number of options held given in ANNCOMP.

6. Adjustment for stock splits

The number of options held and the exercise price need to be adjusted for stock splits. We obtain information on stock splits directly from ExecuComp. When this information is missing we assume that there is no stock split in the given year.

7. Chance to reveal optimism

As discussed above, an executive needs to hold options until one year before expiration in order to be classified as optimistic. If ExecuComp does not cover this time period or if the manager leaves the firm before, there is no chance that optimism can be identified. Therefore, we exclude all executives that have no chance to reveal themselves as being optimistic.

A.4 Variable Definitions

Variable Name	Definition
Managerial Characteristics:	
Optimistic	A dummy variable which equals one if a manager holds executive stock options until the last year of maturity that are at least 40% in-the-money and zero otherwise.
Pre-Optimistic	A dummy variable which equals one in the time period before a manager ever held an option until the final maturity year, which is at least 40% in the money and zero otherwise.
Post-Optimistic	A dummy variable which equals one in the time period after a manager ever held an option until the final maturity year, which is at least 40% in the money and zero otherwise.
Holder67	A dummy variable which equals one if a manager holds options five years after the option grant that are at least 67% in-the-money. This behavior has to be shown at least twice by the manager.
Voluntary Holder	A dummy variable, which equals one if $\frac{Stock\ Holdings}{Salary} >= Median(\frac{Stock\ Holdings}{Salary})$ and zero otherwise, where: Stock holdings is the value of company stock held by the CEO in \$million. Salary is the CEO salary in \$million.
Delta	Overall delta of the option and stock portfolio held by the CEO divided by total shares outstanding. The individual stock delta is one per definition, the delta of an individual option is defined as $e^{-dT}N(Z)$.
Vega	$e^{-dT}N^{'}(Z)ST^{1/2} * (0.01)$. In our regressions we use $log(1+vega)$ to correct for the skewness of vega. where: $Z = \left[ln\left(S/X\right) + T\left(r - d + \sigma^2/2\right)\right]/\sigma T^{1/2}$ N = cumulative probability function for the normal distribution $N^{'}$ =normal density function. S = price of the underlying stock X = exercise price of the option

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Variable Name	Definition
	σ = expected stock-return volatility over the life of the option
	r = natural logarithm of the risk-free rate
	T = time to maturity of the option in years
	d = natural logarithm of expected dividend yield over the life of the option
Female	A dummy variable, which equals one if the CEO is female.
Ph.D.	A dummy variable, which equals one if the CEO holds a Ph.D. degree.
Age	Age of the CEO in years at the time of the debt issue.
Tenure	Time in days since the executive became CEO.
Borrower/Issuer characteristics:	
Total Assets	Firm's total assets in $million.
Leverage	Long-term debt divided by total assets.
Market-to-Book	Market value of the firm divided by the book value of assets.
Tangibility	Net property plant and equipment divided by total assets.
Coverage	Interest expenses divided by EBITDA.
Profitability	EBITDA divided by total assets.
Current Ratio	Current assets divided by current liabilities.
Loan characteristics:	
Facility Amount	Overall facility volume in $million.
Maturity	Time to maturity in months.
Multiple Tranches	A dummy that equals one if the deal consists of more than one tranche and zero otherwise.
Term Loan	A dummy variable, which equals one if the loan type is defined as "Term Loan", "Term Loan A ... Term Loan H", or "Delay Draw Term Loan", and zero otherwise.
Secured	A dummy variable, which equals one if the loan contains collateral
PSD grid characteristics:	
PSD	A dummy variable, which equals one if the loan contract includes a performance pricing provision and zero otherwise.

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Variable Name	Definition
PSD(Rating)	A dummy variable, which equals one if the loan contract includes a performance pricing provision based on the issuer's credit rating and zero otherwise.
PSD(Increasing)	A dummy variable, which equals one if $\frac{(S_i - S_{Min})}{(S_{Max} - S_{Min})} < \frac{1}{3}$ and zero otherwise.
PSD(Mixed)	A dummy variable, which equals one if $\frac{1}{3} >= \frac{(S_i - S_{Min})}{(S_{Max} - S_{Min})} < \frac{2}{3}$ and zero otherwise.
PSD(Decreasing)	A dummy variable, which equals one if $\frac{(S_i - S_{Min})}{(S_{Max} - S_{Min})} >= \frac{2}{3}$ and zero otherwise.
# Pricing Steps	Number of pricing steps defined in the pricing grid.
Local Slope	$0.5 * \left(\frac{(S_{i+1} - S_i)}{(Bond_{i+1} - Bond_i)} + \frac{(S_i - S_{i-1})}{(Bond_i - Bond_{i-1})}\right)$
Local Slope ↑	$\frac{(S_i - S_{i+1})}{(Bond_i - Bond_{i+1})}$
Local Slope ↓	$\frac{(S_{i-1} - S_i)}{(Bond_{i-1} - Bond_i)}$
	where:
	i is the borrower's long-term credit rating as of contract inception
	$i + 1$ is the borrower's long-term credit rating as of contract inception plus one notch (upgrade)
	$i - 1$ is the borrower's long-term credit rating as of contract inception minus one notch (downgrade)
	S_i is the spread that the borrower has to pay given rating i
	S_{i+1} is the spread that the borrower has to pay given rating $i+1$
	S_{i-1} is the spread that the borrower has to pay given rating $i-1$
	S_{Min} is the lowest spread defined in the pricing grid
	S_{Max} is the highest spread defined in the pricing grid
	Bond refers to the market spread for the respective rating notch
Average Slope	Calculated as Local Slope but over all rating notches defined in the pricing grid.
Average Slope ↑	Calculated as Local Slope ↑, but over all credit ratings above the firm's rating at the time of contract inception.
Average Slope ↓	Calculated as Local Slope ↓, but over all credit ratings below the firm's rating at the time of contract inception.

Hold-Up and the Use of Performance-Sensitive Debt

Tim R. Adam   Daniel Streitz

Abstract:

We examine whether performance-sensitive debt (PSD) is used to reduce hold-up problems in long-term lending relationships. We find that the use of PSD is more common in the presence of a long-term lending relationship and if the borrower has fewer financing alternatives available. In syndicated deals, however, the presence of a relationship lead arranger reduces the use of PSD, which is consistent with hold-up being of lesser concern in such cases. Finally, we find a substitution effect between the use of PSD and the tightness of financial covenants. This result also supports our hypothesis that hold-up concerns motivate the use of PSD.

Keywords: Performance-Sensitive debt, Relationship Lending, Hold-Up, Hold-out, Syndicated Debt, Covenants

JEL-Classification: G21, G31, G32

1 Introduction

Since the early 1990s, many bank loans contain performance pricing provisions, which stipulate that the coupon paid rises if the firm's financial performance deteriorates and/or vice versa. Financial performance is measured either by the borrower's credit rating or a financial ratio such as leverage. The theoretical literature has linked the use of performance-sensitive debt (PSD) to debt renegotiation costs, signaling, and asset substitution considerations. Asquith, Beatty, and Weber (2005) argue that PSD reduces debt renegotiation costs due to adverse selection, moral hazard, or unanticipated changes in the borrower's credit risk. Manso, Strulovici, and Tchistyi (2010) demonstrate that PSD can be used as a signaling device for a firm's credit quality in a setting with adverse selection. Finally, Koziol and Lawrenz (2010) show that PSD can mitigate risk-shifting incentives, but Bhanot and Mello (2006) argue that PSD is an inefficient method to reduce incentives for asset substitution.

In this paper we explore a new explanation for the use of PSD. We hypothesize that PSD can be used to mitigate hold-up problems, which, for example, can arise in long-term lending relationships. Sharpe (1990) and Rajan (1992) show that a cost of relationship lending is the potential for hold-up by the lender. The potential for hold-up arises from the information advantage, which the lender acquires in the course of the lending relationship. This information advantage makes it difficult for the borrower to switch to another, less well informed, lender due to adverse selection, which is especially relevant for opaque borrowers with fewer financing alternatives. If the borrower is "locked in", the bank could exploit the situation by charging higher interest rates or by denying interest rate reductions when the borrower's performance improves. Schmidt (2006) argues that the use of covenants, which is common in private debt contracts, further exacerbates the hold-up problem because covenants shift bargaining power from borrowers to lenders. Von Thadden (1995) shows that a solution to this hold-up problem is to pre-specify contract terms ex ante, thereby limiting the discretion of the lender. Indeed, one can view PSD contracts as limiting the discretion of lenders because by pre-specifying the loan contract terms if a borrower's performance deteriorates or improves PSD avoids debt renegotiation in these states. For example, rather than renegotiate a loan after a covenant violation, the performance-pricing provision specifies the outcome of such renegotiation ex ante and thus avoids the situation of a technical default. This argument also implies a substitution effect between the use of PSD and the tightness of covenants.

In syndicated deals, the presence of a relationship lead-arranger is likely to reduce the use of PSD. In the decision to hold-up a client a lender needs to weigh the short-term gains from hold-up against the long-term costs of jeopardizing the relationship. In a syndicated deal, the short-terms gains from hold-up would be shared by all syndicate members, while the long-term costs of jeopardizing the relationship would be borne mostly by the relationship lender. Thus, a relationship lead-arranger should always favor to continue the relationship and benefit from its information advantage relative to other lenders rather than to hold-up a client.

Our paper is the first to explicitly analyze the link between the hold-up problem in repeated lending relationships and the use of PSD contracts. A particular advantage of focusing on lending relationships is that it allows us to differentiate the hold-up from the signaling motivation. This is because signaling is less important in lending relationships, as the relationship lender already has an information advantage (see for example Menkhoff, Neuberger, and Suwanaporn (2006)), while the potential for hold-up rises in lending relationships. Using a large sample of private debt contracts issued by non-financial U.S. borrowers between 1993 and 2011, we show that *accounting-based* PSD contracts, i.e., PSD based on a financial ratio, are about 25% more likely to be used in repeated lending relationships after we control for the endogeneity of the lending relationship. Following Bharath, Dahiya, Saunders, and Srinivasan (2011), we use the spherical distance between the borrower's and the lender's headquarters as an instrument for relationship strength. In contrast, we find that the use of *rating-based* PSD is negatively related to the presence of a repeated lending relationship. Thus, these initial results suggest that accounting-based PSD are used to address hold-up while rating-based PSD is used for signaling.

We further analyze whether the use of PSD varies systematically across different types of borrowers because the potential for hold-up is also a function of borrower characteristics. For example, Santos and Winton (2008) argue that the costs of relationship lending are higher for companies, which do not have access to other financing sources (e.g., bond market access). In line with this argument, we find that accounting-based PSD contracts are more common in relationship lending arrangements with smaller firms, firms that do not have a long-term issuer credit rating at the time of the loan origination, and firms with lower analyst coverage. If a loan is syndicated, performance pricing provisions are more likely, which is consistent with the renegotiation cost argument by Asquith et al. (2005). However, the presence of a lending relationship between the borrower and the lead arranger reduces the use of PSD. This is consistent with the argument that in a syndicate the lead arranger cannot capture all rents from hold-up, causing hold-up to be a less attractive strategy for the lead arranger than to preserve the relationship with the client.

Next, we examine the structure of covenants in PSD because if performance pricing provisions are used to mitigate hold-up problems, then there should be a substitution effect between the pricing grid of rate-increasing PSD[1] and covenant tightness. Covenants should be less tight compared to

[1] PSD that allows for interest rate increases only.

covenants of regular debt.[2] This is what we find. Firstly, the majority of PSD have covenants on the same performance measure as the one used in the performance-pricing provision, with covenant thresholds typically set directly at the end of the pricing grid. Secondly, Debt-to-EBITDA covenants, the most common covenant type in our loan sample, are less tight in PSD contracts that also use Debt-to-EBITDA as a measure of the borrower's performance compared with non-PSD debt contracts. Consistent with the substitution hypothesis, this effect exists only for interest-increasing PSD contracts.[3]

Finally, we examine the evolution of the borrower's credit rating and the borrower's leverage ratio up to 2 years following the issue of PSD, to differentiate hold-up from the possibility that PSD is used to signal credit quality, as proposed by Manso et al. (2010). Under the signaling hypothesis, the firm's performance should improve following a PSD issue, while the hold-up hypothesis makes no prediction about the firm's post-issue performance. We find that borrowers' credit ratings tend to improve and leverage ratios decline 1-2 years following the issue of *rating-based* PSD, but not for *accounting-based* PSD. These results further support our conclusion that accounting-based PSD is used to address hold-up problems in repeated lending relationships, while rating-based PSD is more likely used to signal credit quality.

We make two contributions to the literature. Firstly, we offer a new explanation for the use of PSD, namely that PSD reduces potential hold-up problems in repeated lending relationships. In contrast, Manso et al. (2010) argue that borrowers use PSD to signal their credit quality, while Koziol and Lawrenz (2010) argue that PSD reduces moral hazard. The study that is closest to our own is Asquith et al. (2005), who argue that the use of PSD

[2] Small deteriorations in a borrower's performance, which would otherwise trigger a technical default now automatically lead to interest rate increases as determined by the pricing grid.

[3] Nikolaev (2012) shows that PSD contracts are less likely to be renegotiated than regular debt, which is also consistent with the substitution hypothesis.

reduces debt renegotiation costs. In contrast to renegotiation costs, however, hold-up does not arise in all situations and implies a wealth transfer between borrower and lender.

Secondly, we add to the literature on hold-up in repeated lending relationships. Several authors find evidence that is consistent with the presence of hold-up. Saunders and Steffen (2011) find that private firms pay higher loan spreads than public firms if borrowing from a relationship bank. Hale and Santos (2009) show that banks reduce the interest rates on loans after a client successfully issued its first public bond. Santos and Winton (2008) find that (all else equal) loan spreads of bank-dependent borrowers rise more during recessions than loan spreads of borrowers who have access to public debt markets. Mattes, Steffen, and Wahrenburg (2012) find that capital-constrained (European) banks charge borrowers with high switching costs higher loan spreads than well-capitalized banks. This effect prevails only during recessions. Degryse and Cayseele (2000) find evidence for a deterioration of contract terms over the duration of the lending relationship for a sample of European firms.[4] As argued by Boot (2000), maintaining multiple bank relationships can be one potential solution for this problem.[5] However, Ongena and Smith (2000) show that this may reduce the availability of credit, because increased competition reduces the value of information acquisition and hence the incentive to lend

[4] There is also considerable evidence of the benefits of lending relationships. Petersen and Rajan (1994) find that the duration of a bank-firm relationship does not influence the contracted loan rate, but Berger and Udell (1995) document that rates on lines of credit and collateral requirements decrease with the duration of the bank-firm relationship. Bharath et al. (2011) find that repeated borrowing from the same lender translates into a 10-17 bps lowering of loan spreads, and that relationships are especially valuable when borrower transparency is low. See Boot and Thakor (2000), Elsas and Krahnen (1998), Freudenberg, Imbierowicz, Saunders, and Steffen (2013), Berlin and Mester (1998), Bharath, Dahiyab, Saunders, and Srinivasan (2007), Bharath et al. (2011), and Schenone (2010) for further empirical evidence on the benefits of lending relationships.

[5] Houston and James (1996) find that firms with a single bank relationship use less bank debt, as growth opportunities are higher. Farinha and Santos (2002) find that firms with higher growth opportunities or greater bank dependence are more likely to switch to multiple bank relationships. All of the above-mentioned evidence is consistent with the notion that multiple bank relationships reduce the hold-up problems.

to "young" firms.[6] We extend this literature by linking the use of PSD to the hold-up problem in repeated lending relationships.

The remainder of the paper proceeds as follows. Section 2 presents our hypotheses. Section 3 describes the sample selection process, outlines the construction of variables, and presents some descriptive findings. Section 4 contains the main empirical analysis, which demonstrates a link between relationship lending and the use of performance pricing provisions. Section 5 explores alternative explanations, and Section 6 concludes.

2 Hypothesis Development

Sharpe (1990) and Rajan (1992) show that a long-term lending relationship creates an information asymmetry between the relationship lender and other potential lenders, which can be costly for the borrower. Adverse selection can make it difficult for the borrower to switch to another lender. In this case the relationship lender could take advantage of its information monopoly and extract some rents from the borrower, especially in the event of covenant violations, when much bargaining power rests with the lender (see Chava and Roberts (2008)). Von Thadden (1995) argues that one way of reducing this hold-up problem is to limit the discretion of the lender by using pre-specified contract terms. PSD can be interpreted as such a pre-specification of contract terms. PSD contracts specify higher (lower) interest payments if the borrower's performance deteriorates (improves) in the future. A performance deterioration could trigger a covenant violation, which would subject the borrower to hold-up. In the case of PSD, however, there would be no technical default situation since interest rate increases have been negotiated ex ante in the case of performance deteriorations. Similarly, a performance improvement could

[6] The availability of funds to young firms without a track record is one potential benefit of relationship lending as shown by Petersen and Rajan (1995). Banks can "subsidize" borrowers in earlier periods in return for higher rents in future periods when the banks have an information monopoly.

cause the borrower to request improved loan terms. A relationship lender may hold-up the borrower and deny any changes to the loan terms knowing that the borrower is locked in the relationship. In the case of PSD, however, there would be an automatic adjustment to the loan terms if the borrower's performance changes. Thus, a PSD contract limits the discretion of the lender and therefore can reduce hold-up in long-term lending relationships.[7] This gives rise to our first hypothesis:

Hypothesis 1a *Relationship loans are more likely to include performance-pricing provisions than non-relationship loans.*

In contrast, Manso et al. (2010) argue that PSD is used to signal a firm's credit quality. Relationship lending provides an excellent setting to disentangle the two hypotheses because hold-up is more likely in repeated relationship lending, while the need for signaling is less likely. There is little need to signal if the lender possesses an information advantage already (see Menkhoff et al. (2006)). Thus, if the use for PSD is motivated by signaling considerations, we expect a negative relation between relationship lending and the use of PSD.

Hypothesis 1b *Relationship loans are less likely to include performance-pricing provisions than non-relationship loans.*

Santos and Winton (2008) argue that the severity of the hold-up problem can vary systematically across different types of borrowers. For example, the degree to which a borrower is "locked-in" in a lending relationship depends on the availability of other financing sources, such as public bond market access, and the opaqueness of the borrower. This gives rise to our second hypothesis:

Hypothesis 2 *Firms with fewer outside financing alternatives, which borrow from a relationship lender are more likely to use performance-sensitive debt.*

[7] A performance pricing provision can also be valuable for a lender who is trying to attract high quality borrowers because PSD is a commitment device not to expropriate the borrower ex post.

When renegotiating a loan, a relationship lender must weigh the short-term benefits of holding-up the borrower against the long-term benefits of maintaining the relationship. In syndicated deals the lead arranger must share the benefits of hold-up with the rest of the syndicate, while the benefits of the relationship accrue mostly to the relationship lender. Thus, in a syndicate a relationship lead arranger is less likely to hold-up a borrower, so that the inclusion of performance-pricing provisions should be less likely compared to non-relationship loans. We therefore expect that

Hypothesis 3 *Syndicated relationship loans are less likely to include performance-pricing provisions than syndicated non-relationship loans.*

Covenants especially present an opportunity for hold-up, because after covenant violations, lenders have much bargaining power vis-a-vis their borrowers. The most common consequence of covenant violations is that the coupon the borrower has to pay is revised upward. To eliminate hold-up in these situations, the interest increases could be pre-contracted using performance-pricing provisions. The threshold at which a covenant ultimately kicks in would then have to be set higher than in the absence of a performance-pricing provision. Thus, there is a substitution effect between the use of a pricing grid and the tightness of the respective covenant. We therefore test the following hypothesis.

Hypothesis 4 *Interest-increasing performance-sensitive loans have less tight covenants on the same performance measure, which is also used in the pricing grid.*

Manso et al. (2010) argue that PSD is used to signal a firm's credit quality. If so, a firm's credit quality should improve on average following the issuance of PSD. In contrast, the hold-up hypothesis makes no prediction with respect to the borrower's post issue performance. We therefore test the following hypothesis.

Hypothesis 5 *The issuer's performance improves (does not improve) following the issue of PSD.*

3 Data Description

We obtain our loan sample from the Thomson Reuters Loan Pricing Corporation Dealscan (LPC's Dealscan) database, which contains detailed information on corporate loan issues. We restrict our sample to loans issued by U.S. non-financial borrowers between 1993 and 2011.[8] Consistent with the prior literature (e.g., Berg, Saunders, and Steffen (2013), Bharath et al. (2007)), we conduct our analysis on the facility (tranche) level. We obtain information on loan characteristics such as maturity, the loan amount (scaled by total assets), number of covenants, as well as the loan purpose and loan type. In addition, we record whether a loan is secured or not. We then merge our loan data with borrower-specific information obtained from Standard and Poor's Compustat North America database, such as firm size, market-to-book etc., from the last available fiscal quarter before the loan issue.[9] The Appendix contains the definitions of all variables used in our analysis.

3.1 Performance-sensitive Debt Contracts

The most common performance measure used in PSD contracts is the Debt-to-EBITDA ratio ($\sim$ 48% of all PSD loans issued by U.S. borrowers) followed by the issuer's senior debt rating ($\sim$ 26%). Dealscan also reports the exact pricing grid, i.e., the function, which links the coupon payments to

[8] Prior to 1993, virtually no contracts include a performance-pricing provision according to Dealscan. As PSD clearly existed prior to 1993, we conclude that Dealscan's data quality with respect to PSD is insufficient prior to 1993.

[9] We use Michael Robert's Dealscan-Compustat Linking Database to merge Dealscan with Compustat (see Chava and Roberts (2008)).

the performance measure. Figure 1 shows the pricing grid of a loan issued by Urban Outfitters Inc. in September 2007. The spread paid by Urban Outfitters increases with its Debt-to-EBITDA ratio (an accounting-based PSD). Urban Outfitter's Debt-to-EBITDA ratio at the time of the issue was 4, implying that this loan is an example of a rate-increasing contract. Figure 2 shows the pricing grid of a loan issued by IBM in March 2004. In this contract, the loan spread changes with IBM's senior debt rating (a rating-based PSD). Since IBM's senior debt rating at the time of the issue was A+, this loan is an example of a rate-increasing and rate-decreasing contract.

[Figures 1 & 2 here]

3.2 Measuring Relationship Strength

We follow Bharath et al. (2011) and construct three proxies for the strength of the lending relationship between borrower and lender. To construct these proxies, we first need to identify the lead lender(s) for each loan contract. As in Sufi (2007), we classify a lender as the lead lender if the variable "Lead Arranger Credit" (provided by LPC's Dealscan) takes on the value "Yes", or if the lender is the only lender specified in the loan contract. Next, we search the borrowing record of the borrower over the past five years. The first proxy for the strength of the lending relationship, *Rel(Dummy)*, is a dummy variable, which equals one if the firm borrowed from the same lead lender in the previous five years and zero otherwise.[10] If there are multiple lead lenders in a loan, we calculate the proxy separately for each lender and assign the highest value to the loan. The second proxy, *Rel(Number)*, measures the relative

[10] Dealscan often classifies borrowers at the subsidiary level, e.g., General Electric Capital Canada and General Electric Capital Corp of Puerto Rico are two distinct borrowers in Dealscan. By using the Michael Robert's Dealscan-Compustat Linking Database, all wholly-owned subsidiaries are effectively aggregated under the ultimate parent. We apply the same procedure to lenders. This procedure is important to ensure that, e.g., a switch from Lehman Brothers Inc [Frankfurt] to Lehman Brothers Asia is not classified as an actual lender switch. Not aggregating the borrowers and lenders under the ultimate parent, however, does not affect our results qualitatively.

number of loans obtained from the relationship lender. For bank m lending to borrower i, it is calculated as follows.

$$Rel(Number)_m = \frac{\#\text{ loans by bank } m \text{ to borrower } i \text{ (last 5 years)}}{\text{Total } \#\text{ loans by borrower } i \text{ (last 5 years)}} \tag{1}$$

Again, the highest value is assigned to a loan if there are multiple lead lenders. The third proxy, *Rel(Amount)*, measures the relative loan amounts (in \$) obtained from the relationship lender. For bank m lending to borrower i, it is calculated as follows.

$$Rel(Amount)_m = \frac{\text{Loan amount by bank } m \text{ to borrower } i \text{ (last 5 years)}}{\text{Total loan amount by borrower } i \text{ (last 5 years)}} \tag{2}$$

Again, the highest value is assigned to a loan if there are multiple lead lenders.

3.3 Measuring the Tightness of Covenants

As noted by Demiroglu and James (2010), covenant slack, i.e., the difference between the covenant variable at the initiation of the loan agreement and the covenant threshold, is an intuitive measure of covenant tightness. However, the degree of tightness also depends on the volatility of the covenant variable and is thus firm-specific. We therefore follow Dichev and Skinner (2002) and define covenant tightness as the difference between the covenant variable at the initiation of the loan agreement and the covenant threshold, normalized by the standard deviation of the covenant variable over the previous 8 years.[11]

[11] The tightness of covenants can also be measured by a covenant intensity index that ranges from zero to six, with higher values indicating stricter covenants as proposed by Bradley and Roberts (2003). The index is constructed by summing indicator variables on dividend restrictions, equity sweep, asset sweep, debt sweep, securitization and a binary variable that equals one if the contract includes two or more financial covenants. Murfin (2012) further considers covariation between the different covenant variables when measuring contract strictness. We do not use these indices because we are interested in the tightness of a particular covenant rather than general covenant tightness.

Since various definitions of leverage and liquidity ratios are used in practice, we restrict our analysis to covenants on the Debt-to-EBITDA ratio, which, as Dichev and Skinner (2002) note, has the most consistently used definition.

3.4 Descriptive Statistics

Table 1 presents descriptive statistics for our sample consisting of 25,900 loan tranches issued by 4,958 distinct borrowers between 1993 and 2011. Following Bharath et al. (2011), the data are winsorized at the 1% and 99% levels to remove outliers. Panel A reports loan characteristics, which are consistent with prior studies (e.g. Sufi (2007)). For example, the mean/median tranche amounts in our sample are $314/$110 million, which is large given the mean/median book value of assets of $3,287/$657 million and an average leverage ratio of 29%. The average all-in-drawn spread is 204 basis points, and the average maturity is 3.75 years. 74% of loan tranches are credit lines. Consistent with Manso et al. (2010), roughly 47% of loans include a performance-pricing provision. Panel B reports borrower characteristics. In 55% of cases, borrowers do not have a credit rating, but if a rating exists it tends to be around the investment grade threshold. Panel C reports descriptive statistics on the three relationship lending proxies. A lending relationship exists in 62% of all loan contracts. On average, 42% of the total capital raised over the course of 5 years was raised from the same lead lender.

[Table 1 here]

Table 2 shows the various performance measures used in PSD contracts. The most common performance measure is the Debt-to-EBITDA ratio (48%), followed by the senior debt rating (26%). The remaining performance measures are mostly other leverage ratios. In at least 4% of cases, multiple performance measures are used. We define PSD as accounting-based PSD whenever a financial ratio is used as a measure of firm performance. Rating-based PSD comprise all PSD contracts, which use the borrower's credit rating as a performance measure.

[Table 2 here]

4 Results

4.1 Lending Relationships and the Use of Performance-sensitive Debt

We begin by analyzing the interaction between lending relationships and the choice between PSD and straight debt. As noted in Section II, we distinguish between accounting-based and rating-based PSD. We therefore estimate a multinomial logistic regression.

$$PSD_{it} = \alpha + \alpha_{Ind} + \alpha_t + \alpha_{Rat} + \beta * Rel(M)_{it} + \gamma * X_{it} + \epsilon_{it} \tag{3}$$

The dependent variable, PSD, is a discrete variable, which equals one if the loan contract contains a performance pricing provision on an accounting measure, two if the loan contract includes a performance pricing provision on the borrower's credit rating, and zero in the case of straight debt (control group). $Rel(M)$ represents one of our three measures of relationship strength, and X are control variables to control for heterogeneity in borrower and loan characteristics. We use firm size, measured by the log of total assets, the market-to-book ratio of assets, leverage, tangibility, profitability, the current ratio, the loan amount (scaled by total assets), the deal maturity, and an indicator variable for secured loans as control variables. We also include loan purpose and loan type indicators, time fixed effects, industry fixed effects, and dummy variables for each rating level. We cluster the standard errors at the firm level to account for non-independent observations within firms. Table 3 reports the regression results.

[Table 3 here]

Consistent with Hypotheses 1a and 1b, we find that relationship strength is positively and significantly correlated with the use of accounting-based PSD and negatively related to the use of rating-based PSD. These results suggest that accounting-based PSD may be used to address hold-up, while rating-based PSD may be used for signaling. This conclusion is intuitive on two accounts. First, there are virtually no covenants on a borrower's credit rating, while covenants on accounting ratios are common. Since covenant violations are a cause for hold-up, any PSD that is to reduce the potential for hold-up must be accounting-based rather than rating-based. Second, there is less need for signaling in the presence of a lending relationship because the relationship lender already has an information advantage with respect to other lenders. Therefore, any PSD that is used for signaling should be observed less frequently in the presence of lending relationships.[12]

Consistent with the existing literature on PSD (e.g., Tchistyi, Yermack, and Yun (2011)), larger loan amounts are more likely to include a performance-pricing provision. Loan maturity is positively correlated with the use of accounting-based PSD, which is consistent with Asquith et al. (2005)'s hypothesis that performance-pricing provisions are used in contracts with a higher renegotiation likelihood. Loan contracts are more likely to be renegotiated the longer the maturity. Larger borrowers are less likely to include an accounting-based performance-pricing provision in the loan contract, possibly because large borrowers have more financing alternatives and therefore are less subject

[12] When further distinguishing between interest-increasing, interest-decreasing, and mixed PSD, we find that all three types of accounting-based PSD are positively correlated with relationship strength. These results are available from the authors upon request.

to hold-up. These initial results show that it is accounting-based PSD contracts, which may be motivated by hold-up due to lending relationships, while rating-based PSD are unlikely to be motivated by hold-up considerations. In the following analysis, we therefore exclude rating-based PSD and return to the issue of signaling in Section IV.

The analysis so far presents mostly cross-sectional evidence. However, our control variables may not fully capture all differences between relationship and non-relationship borrowers. If unobservable differences between borrower types are correlated with the use of PSD, our estimates are biased. We therefore include firm-fixed effects to control for unobservable time-invariant differences across firms, and analyze the use of PSD across loans *within* firms. The results of linear probability models relating the use of accounting-based PSD to measures of relationship strength are reported in Table 4.[13]

[Table 4 here]

Confirming our previous findings, relationship strength is positively and significantly correlated with the use of accounting-based PSD, even after controlling for time-invariant differences across firms. The economic magnitude is slightly lower when compared to the cross-sectional results. We include firm-fixed effects in all of the remaining analysis. However, all results remain qualitatively similar if we exclude firm-fixed effects and focus purely on the cross-sectional differences.

The decision to form and stay in a lending relationship is clearly an endogenous choice, which has been recognized in a number of recent studies, e.g. Agarwal and Hauswald (2010), Bharath et al. (2011), Coval and Moskowitz (2001), Dass and Massa (2011), Degryse and Ongena (2005), Norden and Weber (2010), and Petersen and Rajan (2002). We follow this literature and use

[13] We use linear probability models because of the large number of fixed effects. However, all results reported in this paper remain virtually unchanged if we use logit models.

the geographic distance between the borrower and the lead lender as an instrument for relationship strength. This instrument is likely to be correlated with the decision to form a lending relationship but unlikely to be correlated with the decision to include a performance-pricing provision in the loan contract. Lenders that are physically closer to a borrower are more likely to have better information about a borrower, and are hence more likely to become a relationship lender. We match the location of the borrowers' and lenders' headquarters, provided by Dealscan, to the MaxMind World Cities Database to obtain information on the longitude and latitude.[14] We are always able to identify the lender and the borrower location in MaxMind if the information on the location is provided by Dealscan. We treat observations as missing if the exact location of the lender or the borrower is not specified in Dealscan, which reduces the sample by 2,804 observations. We calculate the distance in miles between the borrower and the lead lender for each deal.[15] We follow Petersen and Rajan (2002) and address skewness in the distance measure by using $ln(1 + Distance)$ in the regressions.

Table 5 reports the results of the IV-estimation using linear probability models in computing 2SLS estimates and correcting the standard errors for heteroskedasticity.[16] Consistent with Bharath et al. (2011), we find that $ln(1 + Distance)$ is significantly negatively correlated to all three proxies for lending relationship strength, confirming the validity of the inclusion restriction. The results of the second stage regressions confirm our previous results that PSD contracts are more likely to be used in the presence of bank lending relationships. In fact, PSD contracts are about 25% more likely to be used in

[14] The MaxMind database contains geographical information for about 3 million places in 234 countries and is publicly available at http://www.maxmind.com/app/worldcities.

[15] We use the same estimation formula as in Dass and Massa (2011). We assign the minimum distance to the deal in case of multiple lead lenders. See the Appendix for further details.

[16] Angrist and Pischke (2009) argue that this procedure yields consistent estimates. Several studies find that linear probability models produce results similar to partial effects from more precise models (see e.g., Angrist and Pischke (2009) and Katz, Kling, and Liebman (2001)). However, our results are not sensitive to the question of whether we use linear probability models or bivariate probit models as advocated by Heckman (1978).

repeated lending relationships after we control for the endogeneity of the lending relationship, which is statistically and economically highly significant.[17]

[Table 5 here]

Our results so far show that relationship lending is positively correlated with the use of accounting-based PSD. To establish whether this positive correlation is due to hold-up, we make use of the fact that the severity of the hold-up problem is likely to vary systematically across different types of borrowers. For example, more opaque borrowers have fewer financing alternatives, so that these borrowers are more subject to hold-up. Following Bharath et al. (2011), we use firm size as well as a dummy variable which equals one if the borrower does not have a S&P rating (and zero otherwise) as proxies for firm opacity. Another proxy for opacity is the number of analysts following the firm. Larger firms, rated firms, and firms with larger analyst coverage are more likely to have multiple financing alternatives, and are thus less "locked-in" in a bank lending relationship.

To test for the cross-sectional variation in the severity of the hold-up problem induced by lending relationships, we estimate the following model.

$$\begin{aligned} PSD_{it} = \alpha_i + \alpha_t + \alpha_{Rat} + \beta_1 * Rel(M)_{it} + \beta_2 * BorrowerOpacity_{it} \\ + \beta_3 * Rel(M)_{it} * BorrowerOpacity_{it} + \gamma * X_{it} + \epsilon_{it} \end{aligned} \tag{4}$$

BorrowerOpacity stands for the above-mentioned proxies for borrower opacity. We include interaction variables of relationship strength and *Borrower*

[17] As in other studies that use instruments in relationship lending settings, the economic significance strongly increases in the IV-estimation. For example, Bharath et al. (2011) use IV regressions to examine the impact of lending relationships on loan spreads and find that the effect is more than 5 times stronger when using the distance between borrower and lender as an instrument for relationship lending. Berger, Miller, Petersen, Rajan, and Stein (2005) use IV regressions to examine the relationship between bank size and the exclusivity of bank-borrower relationships. Instrumenting bank size, they show a large increase in economic importance of bank size when compared to the OLS estimates.

Opacity to test for the joint effect of these two variables. Due to the high correlation of the interaction variables, we include one variable at a time in the regressions. The results are reported in Table 6.

[Table 6 here]

The coefficients of all interaction variables of borrower opacity are negative and statistically significant, which supports our hypothesis that opacity in the presence of a lending relationship increases the severity of hold-up, and hence the likelihood of using PSD.[18]

A significant portion of our sample consists of syndicated loans. Asquith et al. (2005) argues that the use of PSD should be more likely in syndicated loans because their renegotiation costs are higher. As reported in Table 6, we find the use of performance-pricing provisions is indeed more likely in syndicated deals. According to *Hypothesis 3*, a relationship lead arranger should find it less beneficial to hold-up a borrower compared to a single lender because the gains from hold-up would have to be shared with the rest of the syndicate. As a result, the use of performance-pricing provisions should be less likely if the lead arranger is a relationship bank. The results reported in Table 6 confirm this hypothesis. The coefficient on *Rel(Dummy)*Syndication* is negative and statistically highly significant.

A potential concern is that the syndication results are driven by the largest banks in the syndicated loan market. The market for syndication is dominated by three large banks (see Ross (2010)). Performance-sensitive debt should be less frequently used if the lending relationship is with one of these banks, because the top 3 banks are mostly transaction-oriented, so that hold-up problems are less severe in relationships with these lenders. We find that

[18] Our results are robust to using our other measures of relationship strength and to excluding all syndicated loans from the sample. These results are available from the authors upon request.

our results still hold if we exclude all loans made by the top 3 banks from our sample.[19]

4.2 Performance-sensitive Debt and Covenants

In this section, we investigate whether there is a substitution effect between the use of performance pricing grids and the tightness of financial covenants. In particular, *Hypothesis 4* states that PSD contracts should have less tight covenants because the pricing grid pre-specifies the consequences of small changes in a borrower's performance, while only large performance deteriorations trigger a renegotiation due to covenant violations.

[Table 7 here]

Table 7 compares the covenant threshold levels used in PSD and non-PSD contracts. We find that PSD contracts have leverage and liquidity covenants with lower default thresholds than non-PSD contracts. For example, the median Debt-to-EBITDA covenant level for PSD contracts is 3.55, and 4 for non-PSD contracts. This appears not to be supportive of *Hypothesis 4*. However, PSD and non-PSD are not unconditionally comparable, since borrower characteristics differ. A multivariate analysis is called for.

Furthermore, we now need to distinguish between interest-increasing and interest-decreasing PSD, because only interest-increasing PSD contracts should have an effect on covenant tightness. Interest-decreasing performance-pricing provisions matter only if a borrower's performance improves. To ensure that covenants and a loan's performance-pricing grid are based on the same variable, we restrict our analysis to covenants on the Debt-to-EBITDA ratio, which is the most frequently used performance measure in our sample.

[19] These results are available from the authors upon request.

Following Dichev and Skinner (2002), we calculate the covenant tightness as the absolute difference between the Debt-to-EBITDA ratio at the initiation of the loan agreement and the Debt-to-EBITDA covenant threshold, normalized by the standard deviation of the borrower's Debt-to-EBITDA ratio over the previous 8 years.[20] A lower ratio indicates a tighter covenant. We then estimate the following regression by OLS.

$$\begin{aligned} Tightness_{it} = \alpha_i + \alpha_t + \alpha_{Rat} + \beta_1 * IncreasingPSD_{it} \\ + \beta_2 * MixedPSD_{it} + \beta_3 * DecreasingPSD_{it} + \gamma * X_{it} + \epsilon_{it} \end{aligned} \tag{5}$$

The dependent variable, *Tightness*, is the tightness of the Debt-to-EBITDA covenant as defined above. X represents loan and borrower characteristics. As before, we control for firm, time, loan purpose, loan type, and rating fixed effects. *IncreasingPSD* is a dummy variable which equals one if the loan contains a pricing grid on Debt-to-EBITDA that only allows for interest rate increases. *DecreasingPSD* is a dummy variable which equals one if the loan contains a pricing grid on Debt-to-EBITDA that allows for interest rate decreases only, and *MixedPSD* is a dummy variable which equals one if the loan contains a pricing grid on Debt-to-EBITDA that allows for both interest rate increases and decreases.

[Table 8 here]

As shown in Table 8, we find that interest-increasing PSD contracts have significantly less tight Debt-to-EBITDA covenants than straight debt. This is consistent with our hypothesis that performance-pricing affects covenant tightness: small changes in the credit risk of the borrower are regulated by performance-pricing provisions and not by tight covenants. We further find

[20] We lose observations because we require 8 years before the loan issue with non-missing observations on the Debt-to-EBITDA ratio to calculate the Debt-to-EBITDA standard deviation.

that more highly levered borrowers have tighter Debt-to-EBITDA covenants. Borrowers with more growth opportunities have less tight covenants.[21]

5 Robustness: Hold-up vs. Signaling

Manso et al. (2010) show that PSD can be used as a signaling device to signal a firm's credit quality. Only borrowers who expect their credit ratings not to deteriorate are willing to enter into contracts that stipulate interest rate increases should the firm's credit rating decline. To test whether signaling explains the use of PSD, Manso et al. (2010) analyze the post-issue credit rating development for firms that issue PSD vs. firms that issue straight debt. We use a similar methodology and further analyze the post-issue development of the firm's leverage ratio. We use the Debt-to-EBITDA ratio to measure leverage as this is the most common performance measure used in accounting-based PSD contracts. We distinguish between accounting-based and rating-based PSD in all specifications, because the signaling hypothesis should predominantly apply to rating-based PSD, while the hold-up hypothesis predominantly applies to accounting-based PSD. In particular, we estimate the following regression.

$$\Delta Performance_{it+1} = \alpha_i + \alpha_t + \beta_1 * PSD(Rating)_{it} + \beta_2 * PSD(Accounting)_{it} + \gamma * X_{it} + \epsilon_{it} \tag{6}$$

$\Delta Performance_i$ is a dummy variable that equals 1 if the borrower's credit rating improves in the first k quarters after the loan issue and 0 otherwise ($k = 4,\ 8$). In an alternative specification, $\Delta Performance_i$ is the difference between the firm's Debt-to-EBITDA ratio k quarters after the loan issue and the firm's Debt-to-EBITDA ratio at the time of the loan issue ($k = 4,\ 8$).

[21] The accuracy and coverage of covenants reported in the Dealscan database has improved over time. However, our results are not sensitive to this issue and remain virtually unchanged if we restrict the sample to loans issued after 2000. These results are available upon request.

$PSD(Rating)$ is a dummy variable, which equals one if the loan contains a pricing grid on the borrower's credit rating, while $PSD(Accounting)_i$ is a dummy variable which equals one if the loan contains a pricing grid on an accounting measure. The regression results are reported in Table 9.

[Table 9 here]

Consistent with the results reported by Manso et al. (2010), we find that firms are more likely to experience a rating improvement up to two years after issuing rating-based PSD relative to borrowers who issued regular debt. Furthermore, firms that issue rating-based PSD see their leverage ratios decline by more than borrowers who issue straight debt. However, these results do not hold for accounting-based PSD. Neither credit ratings nor leverage ratios vary systematically after firms had issued accounting-based PSD. Accounting-based PSD contracts are thus unlikely to be motivated by signaling considerations.

6 Conclusion

Von Thadden (1995) argues that pre-specifying loan contract terms can be an efficient way to mitigate hold-up problems in long-term lending relationships. An example is performance-sensitive debt (PSD), which pre-specifies loan contract terms in events that would otherwise trigger debt renegotiations. In this paper, we test the hypothesis that PSD is used to reduce potential hold-up problems in bank lending relationships.

Consistent with this hypothesis, we find that accounting-based PSD contracts are 25% more likely to be used in relationship lending arrangements, after controlling for the endogeneity of the lending relationship. This is especially the case if the borrower is opaque and/or has fewer financing alternatives, both of which imply a greater potential for hold-up. Syndicated deals are more likely to include performance-pricing provisions, which is consistent with the renegotiation cost argument by Asquith et al. (2005). However, relationship lenders as lead arrangers should find it less beneficial to hold-up a borrower as the gains from hold-up would have to be shared with the other syndicate members. This reduces the need for PSD. Indeed, we find that in syndicated relationship lending the use of PSD is less likely.

We also find a substitution effect between the pricing grid and the tightness of covenants. The Debt-to-EBITDA covenants of interest rate increasing PSD contracts are less tight than the covenants of non-PSD contracts. This substitution effect is consistent with the recommendation by Von Thadden (1995) to pre-specify contract terms to mitigate hold-up.

In contrast to accounting-based PSD, we find no evidence that the use of rating-based PSD is motivated by hold-up considerations. In fact, several results are consistent with rating-based PSD used for signaling. Therefore we conclude that hold-up is likely an important determinant in the decision to issue accounting-based PSD, while signaling motivates the decision to issue rating-based PSD.

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Appendix

A.1 Figures

Figure 1: Accounting-Based PSD

This figure shows the pricing grid of a loan issued by Urban Outfitters Inc in 2007. The spread is contingent on the issuer's Debt-to-EBITDA ratio. The Debt-to-EBITDA ratio at the time of loan issue was 4. The initial spread paid was LIBOR + 150bp.

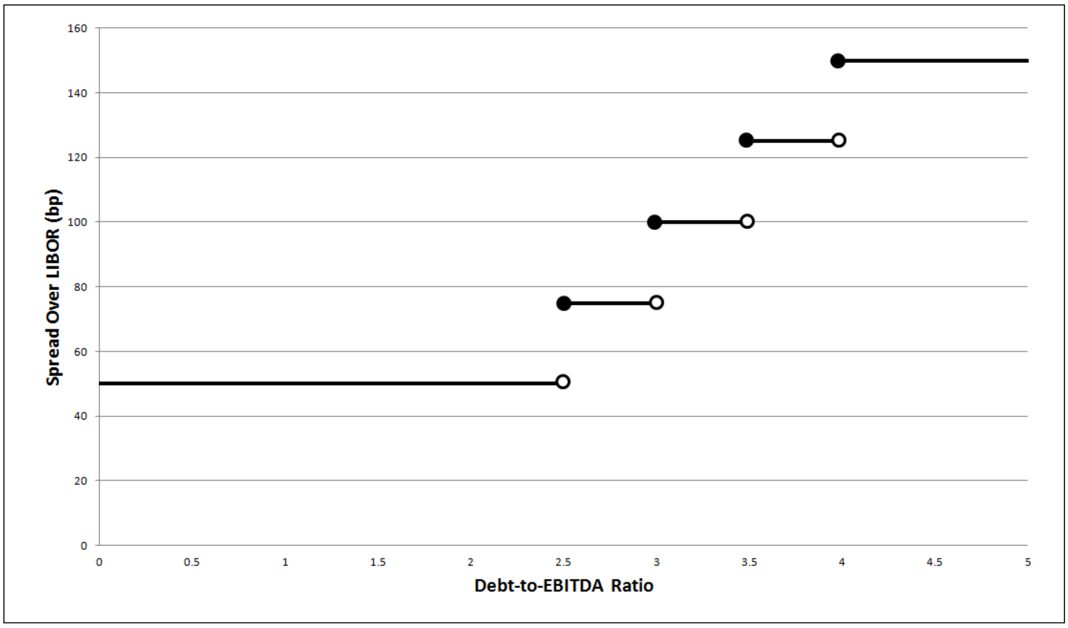
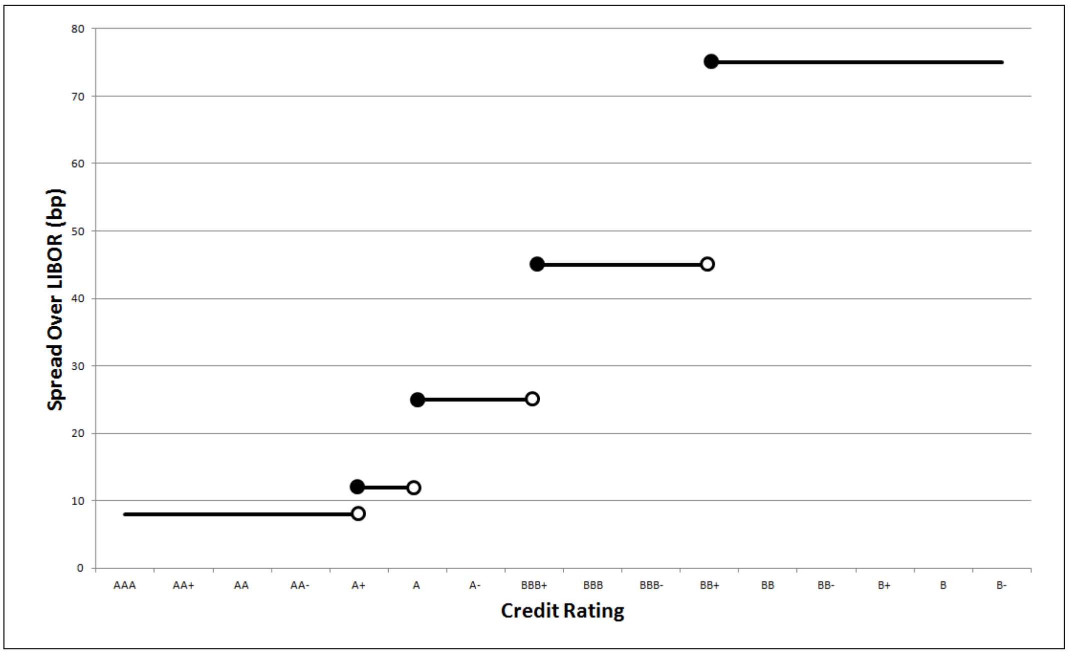


Figure 2: Rating-Based PSD

This figure shows the pricing grid of a loan issued by IBM in March 2004. The loan spread is a function of IBM's S&P senior debt rating. IBM's senior debt rating at the time of loan issue was A+. The initial spread paid was LIBOR + 12bp.



A.2 Tables

Table 1: Summary Statistics

This table reports summary statistics for a sample of 25,900 loan tranches issued by 4,958 non-financial firms between 1993 and 2011. All items are defined in the Appendix, Table A.I.

	Mean	Median	Std	Min	Max	N
PSD(Rating)	0.13	0.00	0.34	0.00	1.00	25900
PSD(Accounting)	0.34	0.00	0.47	0.00	1.00	25900
Facility Amount (mill. USD)	313.83	110.00	745.93	0.04	30000.00	25900
All-in-drawn Spread (bp)	203.66	175.00	147.55	2.70	1655.00	25900
Facility Maturity (months)	45.11	48.00	24.05	1.00	276.00	25900
Term Loan	0.26	0.00	0.44	0.00	1.00	25900
Secured	0.55	1.00	0.50	0.00	1.00	25900
Sole Lender	0.11	0.00	0.32	0.00	1.00	25900
Purpose: General	0.31	0.00	0.46	0.00	1.00	25900
Purpose: Refinance	0.20	0.00	0.40	0.00	1.00	25900
Purpose: Takeover	0.13	0.00	0.33	0.00	1.00	25900
Purpose: Working Capital	0.18	0.00	0.38	0.00	1.00	25900
Panel B: Borrower Characteristics						
Total Assets (mill. USD)	3287.02	657.20	6653.38	10.35	32009.00	25900
Leverage	0.29	0.26	0.23	0.00	4.35	25900
Market-to-Book	1.71	1.41	0.96	0.68	6.38	25900
Tangibility	0.34	0.28	0.24	0.00	0.91	25900
Profitability	0.14	0.13	0.20	-1.20	0.73	25900
Current Ratio	1.86	1.57	1.21	0.25	8.17	25900
# Analysts	4.38	0.00	6.65	0.00	42.00	25900
Rating AAA	0.00	0.00	0.06	0.00	1.00	25900
Rating AA	0.01	0.00	0.12	0.00	1.00	25900
Rating A	0.08	0.00	0.28	0.00	1.00	25900
Rating BBB	0.13	0.00	0.33	0.00	1.00	25900
Rating BB	0.13	0.00	0.34	0.00	1.00	25900
Rating B	0.09	0.00	0.28	0.00	1.00	25900
Rating C (or below)	0.01	0.00	0.08	0.00	1.00	25900
Rated	0.45	0.00	0.50	0.00	1.00	25900
Panel C: Relationship Lending Proxies						
Rel(Dummy)	0.62	1.00	0.49	0.00	1.00	25900
Rel(Number)	0.39	0.38	0.37	0.00	1.00	25900
Rel(Amount)	0.42	0.45	0.39	0.00	1.00	25900

Table 2: PSD Contract Types

This table reports the types and frequencies of performance-pricing provisions used in our sample of PSD.

	Frequency	Observations
Panel A: Accounting-Based PSD		
Debt-to-EBITDA	0.48	5859
User Condition	0.06	727
Multiple	0.04	518
Leverage	0.04	461
Senior Debt to Cash Flow	0.03	384
Fixed Charge Coverage	0.02	267
Other Accounting Measures	0.02	242
Outstandings	0.02	219
Debt-to-Tangible Net Worth	0.01	178
Interest Coverage	0.01	148
Panel B: Rating-Based PSD		
Senior Debt Rating	0.26	3094
Other Credit Rating	0.00	21
Total	1.00	12134

Table 3: Lending Relationships and the Use of Performance-Sensitive Debt

This table reports the marginal effects of multinominal logit regressions to evaluate the likelihoods of using rating-based or accounting-based PSD. The dependent variable equals one if the loan includes a performance pricing provision based on the credit rating of the borrower, two if the loan includes a performance pricing provision based on an accounting measure and zero for non performance-sensitive loan contracts. Marginal effects for each covariate are constructed as the difference in predicted probabilities for a particular outcome computed at their mean values holding all other covariates constant. All items are defined in the Appendix Table A.I. Standard errors are heteroskedasticity robust and clustered at the firm level to account for non-independent observations within firms. *,**,*** Indicate statistical significance at the 10%, 5%, 1% level.

	(1)		(2)		(3)	
	PSD(Accounting)	PSD(Rating)	PSD(Accounting)	PSD(Rating)	PSD(Accounting)	PSD(Rating)
Rel(Dummy)	0.061***	-0.002				
	(0.009)	(0.002)				
Rel(Number)			0.078***	-0.007**		
			(0.011)	(0.003)		
Rel(Amount)					0.072***	-0.008***
					(0.011)	(0.003)
ln(Total Assets)	-0.022***	-0.003	-0.020***	-0.003	-0.020***	-0.003
	(0.005)	(0.002)	(0.005)	(0.002)	(0.005)	(0.002)
Leverage	-0.086***	-0.016**	-0.078***	-0.017**	-0.078***	-0.017**
	(0.021)	(0.008)	(0.021)	(0.008)	(0.021)	(0.008)
Market-to-Book	0.003	0.003	0.003	0.003	0.003	0.003
	(0.004)	(0.002)	(0.004)	(0.002)	(0.004)	(0.002)
Tangibility	-0.024	0.007	-0.025	0.007	-0.026	0.007
	(0.023)	(0.008)	(0.023)	(0.008)	(0.023)	(0.008)
Profitability	0.227***	0.027**	0.226***	0.027**	0.227***	0.027**
	(0.027)	(0.011)	(0.027)	(0.011)	(0.027)	(0.011)
Current Ratio	0.005	0.000	0.005	0.000	0.005	0.000
	(0.004)	(0.001)	(0.004)	(0.001)	(0.004)	(0.001)
ln(Facility Maturity)	0.175***	0.001	0.174***	0.001	0.175***	0.001
	(0.010)	(0.002)	(0.010)	(0.002)	(0.010)	(0.002)
ln(Facility Amount)	0.069***	0.017***	0.070***	0.017***	0.070***	0.017***
	(0.005)	(0.001)	(0.005)	(0.001)	(0.005)	(0.001)
Secured	0.177***	-0.020***	0.178***	-0.020***	0.178***	-0.020***
	(0.010)	(0.003)	(0.010)	(0.003)	(0.010)	(0.003)
Obs.	25900		25900		25900	
Adj. R^2	0.33		0.33		0.33	
Industry Fixed Effects	Yes		Yes		Yes	
Time Fixed Effect	Yes		Yes		Yes	
Credit Rating Fixed Effects	Yes		Yes		Yes	
Loan Purpose Fixed Effects	Yes		Yes		Yes	
Loan Type Fixed Effects	Yes		Yes		Yes	

Table 4: Lending Relationships and the Use of Accounting-Based PSD - Borrower Fixed Effects

This table reports linear probability models to evaluate the likelihood of using accounting based PSD. The dependent variable equals one if the loan includes a performance pricing provision based on an accounting measure and zero for non performance-sensitive loan contracts. All items are defined in the Appendix Table A.I. Standard errors are heteroskedasticity robust and clustered at the firm level to account for non-independent observations within firms. *,**,*** Indicate statistical significance at the 10%, 5%, 1% level.

	(1)	(2)	(3)	(4)	(5)	(6)
	PSD(Accounting)	PSD(Accounting)	PSD(Accounting)	PSD(Accounting)	PSD(Accounting)	PSD(Accounting)
Rel(Dummy)	0.056***	0.024**				
	(0.008)	(0.010)				
Rel(Number)			0.067***	0.025**		
			(0.010)	(0.013)		
Rel(Amount)					0.063***	0.025**
					(0.010)	(0.012)
ln(Total Assets)	-0.013***	0.008	-0.011**	0.009	-0.011**	0.009
	(0.005)	(0.011)	(0.005)	(0.011)	(0.005)	(0.011)
Leverage	-0.076***	-0.123***	-0.070***	-0.121***	-0.070***	-0.121***
	(0.018)	(0.031)	(0.018)	(0.031)	(0.018)	(0.031)
Market-to-Book	0.004	0.009	0.003	0.009	0.003	0.009
	(0.004)	(0.008)	(0.004)	(0.008)	(0.004)	(0.008)
Tangibility	-0.017	0.070	-0.018	0.069	-0.018	0.069
	(0.021)	(0.068)	(0.021)	(0.068)	(0.021)	(0.068)
Profitability	0.196***	0.133***	0.195***	0.133***	0.195***	0.133***
	(0.019)	(0.044)	(0.019)	(0.044)	(0.019)	(0.044)
Current Ratio	0.005	0.004	0.005	0.004	0.005	0.004
	(0.004)	(0.006)	(0.004)	(0.006)	(0.004)	(0.006)
ln(Facility Maturity)	0.137***	0.101***	0.137***	0.101***	0.137***	0.101***
	(0.007)	(0.009)	(0.007)	(0.009)	(0.007)	(0.009)
ln(Facility Amount)	0.067***	0.048***	0.068***	0.048***	0.067***	0.048***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Secured	0.171***	0.221***	0.171***	0.221***	0.171***	0.221***
	(0.009)	(0.012)	(0.009)	(0.012)	(0.009)	(0.012)
Obs.	22519	22519	22519	22519	22519	22519
Adj. R^2	0.288	0.455	0.288	0.455	0.288	0.455
Firm Fixed Effects	No	Yes	No	Yes	No	Yes
Industry Fixed Effects	Yes	No	Yes	No	Yes	No
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Credit Rating Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Loan Purpose Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Loan Type Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 5: IV-Estimation: Lending Relationships and the Use of Accounting-Based PSD

This table reports the results of instrumental variable (IV) estimations, using *Distance* as an instrument for lending relationships. The sample consists of straight loans and accounting-based performance sensitive loans. The dependent variables in the first stage regressions (Columns (1a)-(3a)) are *Rel(Dummy)*, *Rel(Number)*, and *Rel(Amount)* respectively. The dependent variable in the second stage regression (Columns (1b)-(3b)) is a dummy, which equals one if the loan contract includes an accounting-based performance pricing provision and zero otherwise. All other variables are defined in the Appendix Table A.I. Standard errors are heteroskedasticity robust and clustered at the firm level to account for non-independent observations within firms. *,**,*** Indicate statistical significance at the 10%, 5%, 1% level.

	(1a)	(2a)	(3a)	(1b)	(2b)	(3b)
	First Stage Regressions			Second Stage Regressions		
	Rel(Dummy)	Rel(Number)	Rel(Amount)	PSD(Accounting)	PSD(Accounting)	PSD(Accounting)
ln(1+Distance)	-0.019***	-0.019***	-0.020***			
	(0.003)	(0.002)	(0.002)			
Rel(Dummy)				0.251*		
				(0.146)		
Rel(Number)					0.254*	
					(0.146)	
Rel(Amount)						0.235*
						(0.135)
ln(Total Assets)	0.065***	0.018***	0.024***	0.000	0.012	0.011
	(0.008)	(0.006)	(0.007)	(0.012)	(0.008)	(0.008)
Leverage	0.039	-0.043**	-0.046**	-0.142***	-0.121***	-0.121***
	(0.024)	(0.020)	(0.020)	(0.024)	(0.024)	(0.024)
Market-to-Book	-0.001	-0.002	-0.005	0.013**	0.013**	0.014**
	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
Tangibility	0.015	0.015	0.025	0.143***	0.143***	0.141***
	(0.051)	(0.041)	(0.042)	(0.049)	(0.049)	(0.049)
Profitability	0.091***	0.097***	0.082***	0.115***	0.113***	0.119***
	(0.035)	(0.028)	(0.030)	(0.037)	(0.037)	(0.035)
Current Ratio	-0.012**	-0.010***	-0.013***	0.010**	0.010**	0.010**
	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
ln(Facility Maturity)	-0.031***	-0.025***	-0.026***	0.111***	0.110***	0.110***
	(0.006)	(0.004)	(0.005)	(0.007)	(0.007)	(0.007)
ln(Facility Amount)	0.039***	0.015***	0.025***	0.027***	0.033***	0.031***
	(0.004)	(0.003)	(0.003)	(0.007)	(0.004)	(0.005)
Secured	-0.036***	-0.030***	-0.035***	0.228***	0.226***	0.227***
	(0.009)	(0.007)	(0.007)	(0.010)	(0.010)	(0.010)
Obs.	19715	19715	19715	19715	19715	19715
Adj. R^2	0.376	0.313	0.314	0.144	0.160	0.163
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Credit Rating Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Loan Type Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Loan Purpose Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 6: Borrower Opacity and Loan Syndication

This table reports linear probability models, relating the use of accounting-based PSD to measures of borrower opaqueness. The dependent variable is a dummy variable, which equals one if a loan includes an accounting-based performance pricing provision and zero otherwise. All items are defined in the Appendix Table A.I. Standard errors are heteroskedasticity robust and clustered at the firm level to account for non-independent observations within firms. *,**,*** Indicate statistical significance at the 10%, 5%, 1% level.

	(1) PSD(Accounting)	(2) PSD(Accounting)	(3) PSD(Accounting)	(4) PSD(Accounting)
Rel(Dummy)*ln(Total Assets)	-0.016***			
	(0.005)			
Rel(Dummy)*Rated		-0.039*		
		(0.020)		
Rel(Dummy)*#Analysts			-0.003*	
			(0.002)	
Rel(Dummy)*Syndication				-0.080***
				(0.026)
Rel(Dummy)	0.124***	0.042***	0.024**	0.093***
	(0.034)	(0.013)	(0.012)	(0.025)
ln(Total Assets)	0.016	0.004	0.001	0.006
	(0.011)	(0.011)	(0.011)	(0.010)
Rated		-0.016		
		(0.024)		
#Analysts			0.008***	
			(0.002)	
Syndication				0.140***
				(0.021)
Obs.	22519	22519	22519	22519
Adj. R^2	0.456	0.453	0.457	0.458
Firm Fixed Effects	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes
Credit Rating Fixed Effects	Yes	Yes	Yes	Yes
Loan Purpose Fixed Effects	Yes	Yes	Yes	Yes
Loan Type Fixed Effects	Yes	Yes	Yes	Yes
Loan Characteristics	Yes	Yes	Yes	Yes
Borrower Characteristics	Yes	Yes	Yes	Yes

Table 7: Covenant Thresholds in PSD vs. Non-PSD Contracts

This table reports summary statistics for the initial ratios of covenants types used in accounting-based PSD and non-PSD contracts between 1993 and 2011.

	PSD(Accounting)				Non-PSD			
	Mean	Median	Std	N	Mean	Median	Std	N
Panel A: Leverage Covenants								
Max. Debt-to-Tangible Net Worth	2.32	2.00	1.66	495	2.57	1.60	5.15	1052
Max. Debt-to-EBITDA	3.98	3.55	1.54	5816	4.49	4.00	2.42	2316
Max. Senior Debt-to-EBITDA	3.38	3.25	1.34	1236	3.44	3.25	2.04	581
Max. Debt-to-Equity	1.36	1.00	0.91	40	3.08	1.57	4.84	68
Max. Senior Leverage	0.67	0.60	0.22	7	0.72	0.72	0.20	4
Max. Leverage	0.58	0.55	0.21	906	0.62	0.60	0.36	487
Max. Loan-to-Value	1.89	2.25	1.30	7	0.84	0.75	0.59	15
Panel B: Coverage Covenants								
Max. Cash Interest Coverage	2.02	1.75	0.89	113	1.72	1.40	0.75	69
Min. Debt Service Coverage	1.48	1.25	0.70	688	1.45	1.25	0.58	718
Min. Fixed Charge Coverage	1.37	1.25	0.52	4228	1.32	1.20	0.55	1876
Min. Interest Coverage	2.56	2.50	0.85	3487	2.40	2.25	1.27	1767
Panel C: Liquidity Covenants								
Min. Current Ratio	1.27	1.15	0.38	945	1.37	1.25	0.50	775
Min. Quick Ratio	1.09	1.00	0.52	145	1.29	1.25	0.50	316
Panel D: Other Covenants								
Max. Capex	57.79	20.00	144.89	2249	50.07	10.00	135.52	1672
Min. EBITDA	35.87	15.00	80.42	768	31.95	5.50	110.88	831

Table 8: Debt-to-EBITDA Covenant Tightness

This table presents OLS regressions relating Debt-to-EBITDA covenant tightness to the use of PSD. The sample includes contracts, only which have a covenant on the Debt-to-EBITDA ratio. We further require that all PSD contracts use the Debt-to-EBITDA ratio as a measure of the borrowers performance. All variables are defined in the Appendix Table A.I. Standard errors are heteroskedasticity robust and clustered at the firm level to account for non-independent observations within firms. *,**,*** Indicate statistical significance at the 10%, 5%, 1% level.

	(1) Covenant Tightness	(2) Covenant Tightness	(3) Covenant Tightness	(4) Covenant Tightness
Increasing PSD	2.112***	1.581***	0.932**	0.742*
	(0.534)	(0.522)	(0.450)	(0.441)
Mixed PSD	-0.0249	-0.212	0.335	0.284
	(0.253)	(0.250)	(0.247)	(0.244)
Decreasing PSD	0.137	0.172	0.0604	0.0817
	(0.285)	(0.283)	(0.226)	(0.230)
Debt-to-EBITDA	-0.371***	-0.332***	-0.203***	-0.181***
	(0.0413)	(0.0390)	(0.0349)	(0.0312)
ln(Total Assets)		0.234		0.263
		(0.149)		(0.313)
Market-to-Book		0.890***		0.785***
		(0.182)		(0.278)
Tangibility		0.393		1.858
		(0.580)		(2.103)
Profitability		-0.491		1.161
		(1.036)		(1.487)
Current Ratio		0.266*		0.503*
		(0.142)		(0.273)
ln(Facility Amount)		0.179*		0.0547
		(0.103)		(0.0718)
ln(Facility Maturity)		0.247		0.229
		(0.227)		(0.164)
Secured		-0.812**		0.0266
		(0.318)		(0.291)
Obs.	4996	4996	4996	4996
Adj. R^2	0.200	0.226	0.778	0.784
Firm Fixed Effects	No	No	Yes	Yes
Industry Fixed Effect	Yes	Yes	No	No
Time Fixed Effect	Yes	Yes	Yes	Yes
Credit Rating Fixed Effects	Yes	Yes	Yes	Yes
Loan Purpose Fixed Effects	Yes	Yes	Yes	Yes
Loan Type Fixed Effects	Yes	Yes	Yes	Yes

Table 9: Post Issue Performance

This table reports linear probability models to examine credit rating changes of the borrower after the issue of PSD. The dependent variable equals 1 if the borrower's credit rating improved in the first 4 or 8 quarters after the loan issue and zero otherwise. This table further reports OLS regressions to examine the change in the Debt-to-EBITDA 4 or 8 quarters after the issue of PSD. All variables are defined in the Appendix Table A.I. Standard errors are heteroskedasticity robust and clustered at the firm level to account for non-independent observations within firms. *,**,*** Indicate statistical significance at the 10%, 5%, 1% level.

	(1)	(2)	(3)	(4)
	Rating Upgrade (+4)	Rating Upgrade (+8)	Δ Debt-to-EBITDA (+4)	Δ Debt-to-EBITDA (+8)
PSD(Rating)	0.037***	0.026*	-0.134	-0.063
	(0.012)	(0.014)	(0.092)	(0.085)
PSD(Accounting)	0.008	0.011	0.071	0.029
	(0.016)	(0.020)	(0.087)	(0.091)
ln(Total Assets)	-0.006	-0.008	0.040	0.075
	(0.018)	(0.025)	(0.104)	(0.107)
Leverage	-0.183***	-0.174**	-0.972***	-0.998***
	(0.067)	(0.077)	(0.023)	(0.018)
Market-to-Book	0.096***	0.100***	-0.312***	0.002
	(0.012)	(0.013)	(0.057)	(0.074)
Tangibility	-0.062	-0.016	-0.037	-0.037
	(0.096)	(0.118)	(0.721)	(0.612)
Profitability	0.437***	0.339***	0.315	0.222
	(0.097)	(0.113)	(0.602)	(0.619)
Current Ratio	-0.003	-0.015	-0.028	0.045
	(0.010)	(0.012)	(0.070)	(0.058)
ln(Facility Maturity)	0.005	0.003	-0.007	0.000
	(0.010)	(0.012)	(0.071)	(0.066)
ln(Facility Amount)	0.012***	0.008	0.067**	0.097***
	(0.005)	(0.006)	(0.031)	(0.031)
Secured	-0.050***	-0.080***	0.422***	0.205**
	(0.015)	(0.018)	(0.088)	(0.082)
Obs.	11,057	9,707	24,459	21,839
Adj. R^2	0.308	0.406	0.729	0.758
Firm Fixed Effects	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes
Credit Rating Fixed Effects	Yes	Yes	Yes	Yes
Loan Purpose Fixed Effects	Yes	Yes	Yes	Yes
Loan Type Fixed Effects	Yes	Yes	Yes	Yes

A.3 Variable Definitions

Table A.I: Variable Definitions

Variable Name	Definition (Compustat Item #)	Source
Loan characteristics		
PSD (Rating)	A dummy variable which equals one if the loan tranche includes a performance pricing provision based on the firm's credit rating.	Dealscan
PSD (Accounting)	A dummy variable which equals one if the loan tranche includes a performance pricing provision based on an accounting measure.	Dealscan
Increasing PSD	A dummy variable which equals one if the pricing grid allows for interest rate increases only.	Dealscan
Mixed PSD	A dummy variable which equals one if the pricing grid allows for both interest rate increases and interest rate decreases.	Dealscan
Decreasing PSD	A dummy variable which equals one if the pricing grid allows for interest rate decreases only.	Dealscan
Facility Amount	Facility amount in million USD.	Dealscan
All-in-drawn Spread	Initial all in drawn spread over LIBOR.	Dealscan
Facility Maturity	Time to maturity in Months.	Dealscan

Continued on next page

Table A.I – continued from previous page

Variable Name	Definition (Compustat Item #)	Source
Term Loan	A dummy variable which equals one if the type of the loan tranche is specified as "Term Loan", "Term Loan A ... H", or "Delay Draw Term Loan".	Dealscan
Secured	A dummy variable which equals one if the loan is secured.	Dealscan
Covenant Tightness	(Debt-to-EBITDA - Debt-to-EBITDA-Covenant-Threshold) divided by the standard deviation of Debt-to-EBITDA over the previous 8 years.	Dealscan & Compustat
Purpose: General	A dummy variable which equals one if the loan purpose is specified as "corporate purpose".	Dealscan
Purpose: Refinance	A dummy variable which equals one if the loan purpose is specified as "debt repayment".	Dealscan
Purpose: Takeover	A dummy variable which equals one if the loan purpose is specified as "takeover" of "acquisition".	Dealscan
Purpose: Working Capital	A dummy variable which equals one if the loan purpose is specified as "working capital".	Dealscan
Syndication	A dummy variable which equals one if the distribution method of the loan tranche is defined as "Syndication" according to Dealscan.	Dealscan
Sole Lender	A dummy variable which equals one if the loan tranche is not syndicated (Syndication = 0).	Dealscan

Continued on next page

Table A.I – continued from previous page

Variable Name	Definition (Compustat Item #)	Source
Distance	The spherical distance between the borrower's headquarter and the lender's headquarter in miles. The distance between bank i and borrower j is calculated as follows: $d_{i,j} = arc\ cos(deg_{latlon}) * r$, where: r = the radius of Earth in miles, and $deg_{latlon} = cos(lat_i) * cos(lon_i) * cos(lat_j) * cos(lon_j)$ $+cos(lat_i) * sin(lon_i) * cos(lat_j) * sin(lon_j) + sin(lat_i) * sin(lat_j)$ lat and lon refer to the latitude and longitude in radians (converted from degrees by multiplying with $\pi/180$).	Dealscan & MaxMind
Borrower characteristics		
Total Assets	Firm's total assets in million USD.	Compustat
Leverage	Long-term debt divided by total assets.	Compustat
Market-to-Book	Market value of the firm divided by the book value of assets.	Compustat
Tangibility	Net property plant and equipment divided by total assets.	Compustat
Profitability	EBITDA divided by total assets.	Compustat
Current Ratio	Current assets divided by current liabilities.	Compustat
# Analysts	The number of analysts covering the borrower at the time of the loan origination.	I/B/E/S

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Table A.I – continued from previous page

Variable Name	Definition (Compustat Item #)	Source
Rating AAA ... C(or below)	A dummy variable which equals one if the borrower has an S&P rating of AAA ... C (or below) at the time of the loan issue.	Compustat
Rated	A dummy variable which equals one if the borrower has an S&P rating at the time of the loan issue.	Compustat
Debt-to-EBITDA	Total debt divided by EBITDA.	Compustat
Relationship Lending Proxies		
Rel(Dummy)	A dummy variable which equals one if the firm borrowed from at least one of the lead lenders in the five years before the present loan.	Dealscan
Rel(Number)	The number of loans from the same lead bank(s) over the total number of loans issued in the last five years before the present loan.	Dealscan
Rel(Amount)	The dollar value of loans from the same lead bank(s) over the total dollar value of all loans issued in the last five years before the present loan.	Dealscan